MINISTÉRIO DA EDUCAÇÃO
SECRETARIA DE EDUCAÇÃO PROFISSIONAL E TECNOLOGICA
INSTITUTO FEDERAL DE EDUCAÇÃO, CIÊNCIA E TECNOLOGIA DO SUDESTE DE MINAS GERAIS
CAMPUS AVANÇADO BOM SUCESSO

RELATÓRIO INDIVIDUAL DO DOCENTE - RID

Dados do Docente						
Docente:	Victor Schmidt Comitti				**SIAPE:**	1758559
Departamento	ENSINO				**Núcleo:**	Administração
Telefone:	31-992885368		**E-mail:**	victor.comitti@ifsudestemg.edu.br		
Semestre:	2º	**Ano:**	2019			

Regime de Trabalho:							
Efetivo:	**Substituto/Temporário:**		**20h**		**40h**		**40h DE**

Descreva as Atividades que foram realizadas conforme o planejamento e destaque as diferenças entre o realizado/planejado

Disciplinas

Disciplina	Carga Horária
Climatologia e Meteorologia	2
Metodologia Científica I	4
Fundamentos de administração financeira e contabilidade (FIC)	0.9
Fundamentos de Logística (FIC)	0.9
Ética (FIC)	0.2
-	-
Total	8

Atividades de Preparação e Manutenção do Ensino

Atividade	Carga Horária	Realizado
Estudo, Planejamento e Elaboração de Materiais e Práticas Pedagógicas	2	2
Preparação de Aulas Teóricas e Práticas	2	2
Organização de Material Pedagógico	2	2
Produção e Correção dos Instrumentos de Avaliação	4	4
Registro de Atividades Acadêmicas	2	2
	Total	12

Atividades de Apoio ao Ensino

Atividade	Carga Horária	Realizado
Atendimento de Alunos Extraclasse (física ou virtual)	4	4
Reuniões Pedagógicas, Conselhos de Classe e/ou Reuniões de Pais	-	
Participação Banca de Trabalho de Conclusão de Curso	-	
Atendimento de Alunos em Regime de Exercício Domiciliar	-	
Orientação em Olímpiadas do Conhecimento e/ou Competições Diversas	-	
Organização, Coordenação e/ou Acompanhamento de Visitas Técnicas	-	
Nivelamento sem Constituição de Turma	-	
	Total	4

Atividades de Orientação

Atividade	Carga Horária	Realizado
Orientação de Estágio	-	
Coordenação e Participação como Colaborador em Projeto de Ensino	-	

Orientação Acadêmica	-	
Orientação em Monitorias de Ensino e Iniciação à Docência	-	
Orientação de Trabalhos de Conclusão de Curso	-	2
Orientação ou Coorientação de Mestrado ou Doutorado	-	
Participação na Elaboração e Revisão de Projetos Pedagógicos de Cursos	-	
	Total	2
	TOTAL ATIVIDADES DE ENSINO	**26**

Atividades de Pesquisa e Inovação

Atividade	Carga Horária	Realizado
Coordenação e Participação como colaborador em Projeto de Pesquisa	-	
Orientação de Aluno de Iniciação à Pesquisa Científica e/ou Tecnológica	-	
Coordenação e/ou Participação de Grupo de Pesquisa Cadastrado no CNPq	1	0
Participação de Banca Examinadora de Tese de Doutorado e/ou Dissertação de Mestrado e/ou Monografia de Especialização	-	
Participação de Banca Examinadora de Monografica de Graduação e/ou Trabalho de Conclusão de Curso de Graduação ou de Curso Técnico	-	
Participação de Banca Examinadora de Qualificação de Mestrado ou Douturado	-	
Preparação de Artigo Técnico-Científico a ser publicado em anais de Eventos Acadêmico-Científicos Locais, Regionais, Nacionais ou Internacionais	-	
Preparação de Artigo Técnico-Científico a ser publicado em periódico de circulação local ou nacional	-	
Preparação de Artigo Técnico-Científico a ser publicado em periódico indexado nacional ou internacional	14.5	12
Preparação de Livro ou de Capítulo de Livro Didático, Cultural ou Técnico; Produção de Relatório Técnico, Manival Técnico e/ou Didático com ISBN	-	
Editoração de Revistas Científicas Locais, Regionais, Nacionais ou Internacionais	-	
Editoração, Organização e/ou Tradução de Livros e/ou Periódicos Acadêmicos, Científicos ou Técnicos	-	
Participação em Conselho Editoral Local, Regional, Nacional ou Internacional	-	
Participação, como editor, membro de conselho e/ou parecerista de Publicações Acadêmico Científicas		2
Tradução de Artigo Didático, Cultural, Artístico ou Técnico	-	
Participação em Banco de Avaliadores de Pesquisa, Comitê ou Comissão Científica		2
Consultor ad hoc na Análise de Projetos, em Seleção de Editais	-	
Consultor ad hoc, na Condição de Convidado, em Eventos Acadêmicos	-	
Coordenação ou Participação em Comissão Organizadora de Oficinas, Seminários e outros Eventos Científicos, Locais, Regionais, Nacionais ou Internacional	-	
Participação como Conferencista Convidado em Eventos Científicos, Locais, Regionais, Nacionais ou Internacionais	-	
Participação em Eventos Acadêmicos-Científicos Locais, Regionais, Nacionais e Internacionais	0.5	0.5
Participação em Visita ou Missão Internacional, Devidamente autorizada pela Instituição para Desenvolver Atividades Acadêmicas	-	
Desenvolvimento e Registro de propriedades Imtelectuais ou Inovação Tecnológica Cadastradas no NITTEC, tais como Elaboração, Submissão e Registro de Patentes, Registro de Software, Desenho Industrial ou Projeto Piloto, Entre Outras	-	
Desenvolvimento de Aplicativos Computacionais, Registrados ou Publicados em Livros ou Revistas Indexadas	-	

Organização e/ou Coordenação de Pesquisa de Campo Institucional	-	
Coordenação de Institutos nacionais de Ciência e Tecnologia e Inovação Externos	-	
	TOTAL ATIVIDADES DE PESQUISA:	**16.5**
Atividades de Extensão		
Atividade	Carga Horária	Realizado
Coordenação e Participação como Colaborador em Programas e Projetos de Extensão	-	
Coordenação de Cursos e Eventos de Extensão	-	
Publicação de Pôsters, Resumos e/ou artigos Resultantes de Projetos de Extensão, em Periódicos de Extensão	-	
Prestação de Serviços: Conjunto de Ações, tais como Consultorias, Laudos Técnicos e Assessorias, vinculadas às Áres de Atuação do IF Sudeste MG	-	
Atividades Resultantes de Projetos e Programas de Extensão, Tais como Apresentações em Eventos e Publicações de Caráter Extensionista	-	
Organização e/ou Coordenação de Visitas Técnicas Institucionais de Caráter Extensionista	-	
Coordenação e/ou Participação de Grupos de Estudos em Ativiades de Extensão Cadastrados na Diretoria de Extensão	-	
Relatório, Parcial ou Final, de Atividades Locais, Regionais, Nacionais ou Internacionais de Extensão	-	
Orientação de Alunos em Cumprimento de Atividades e/ou de Projetos de Extensão	-	
Coordenação de Núcleos de Estudos Interdisciplinares	-	
Tutoria de Empresas Juniores	-	
Atividades em Cursos e Eventos de Extensão Aprovados e Cadastrados na PROEX ou Diretorias de Extensão	-	
Preparação de Trabalho a ser Apresentado em Eventos Artísticos-Culturais	-	
Editoração de Revistas Culturais, de Extensão Locais, Regionais, Nacionais ou Internacionais	-	
Participação como Conferencista Convidado em Eventos Desportivos ou Artístico-Culturais, Locais, Regionais, Nacionais ou Internacionais	-	
Atividades de Assessoria, Minicursoen Congresso, Consultoria, Perícia ou Sindiância cadastradas na PROEX e ou Diretorias de Extensão	-	
Participação em Concertos, Recitais e Apresentações Diversas como Instrumentista, Orquestradorm Arranjador, Compositor, Regente ou Solista	-	
Produção Artística em Mídia: Documentarios e/ou Material Didático, Programa de Televisão, Rádio, Video ou Videoconferência, Gravação e Edição de CD, DVD ou Outras Mídias	-	
Direção e Montagem de Espetáculos Musicais, Teatrais, Dança e Exposições Apresentadas ao Público	-	
Outras Atividades de Natureza Similar	-	
	TOTAL ATIVIDADES DE EXTENSÃO:	**0**
Atividades de Gestão Institucional e Representações		
Atividade	Carga Horária	Realizado
Diretorias Sistêmicas, Chefias e Coordenadorias e Ensino, Pesquisa e Extensão, Planejamento Institucional	-	
Atividades de Coordenação de Curso	-	
Atividades de Chefia ou Coordenação de Laboratório de Pesquisa, Ensino, Desenvolvimento Tecnológico e/ou Inovação	-	
Atividades Referentes aos Processos de Cotação, Compra, Conferência de Materiais de Processos Licitatórios	-	

Atividades não Remuneradas de Participação em Comissões Permanentes, Comitês, Fóruns e Representações Internas e Externas ao IF Sudeste MG	-	1
Representação Acadêmica e Participação em Órgãos de Formulação e Execução de Políticas Públicas de Ensino, Ciência e Tecnologia e de Políticas Sociais	-	
Atividades de Participação em Comissões Temporarias	-	
Atividades de Representação Interna tais como Colegiados, Conselhos, Núcleos e Docentes Estruturantes	-	
Atividade de Representação Externa	-	
Representação na Entidade Sindical ou de Associação de Docentes que Legalmente Representa a Categoria	-	
Atividades de Participação em Banca Examinadora de Concurso Público para Professor Efetivo, Processos Simplificados de Docentes, bem Como Bancas de Seleção de Estagiários	-	
Participação em Banca Examinadora de Seleção de Doutorado, Mestrado e Especialização	-	
TOTAL ATIVIDADES DE GESTÃO INSTITUCIONAL E REPRESENTAÇÕES:		**1**

Atividades de Qualificação e Capacitação

Atividade	Carga Horária	Realizado
Curso de Graduação	-	
Curso de Pós-Graduação	-	
Curso de Mestrado	-	
Curso de Doutorado	-	
Curso de Capacitação	-	
TOTAL ATIVIDADES DE QUALIFICAÇÃO E CAPACITAÇÃO:		**0**
TOTAL HORAS PID:		**43.5**

OBSERVAÇÃO / JUSTIFICATIVA

Bom Sucesso 18 de Março de 2020

ASSINADO E/OU AUTENTICADO PELO PROFESSOR(A) E PELAS CHEFIAS IMEDIATAS PROFESSOR DÊNISSON NEVES MONTEIRO SIAPE 1857310, GRAZIANY THIAGO FONSECA SIAPE 19669046 E PROFESSOR ROBSON JOSÉ DA SILVA SIAPE 2047063

X

Portal do Docente

INSTITUTO FEDERAL DE EDUCAÇÃO, CIÊNCIA E TECNOLOGIA DO SUDESTE DE MINAS GERAIS
SISTEMA INTEGRADO DE GESTÃO DE ATIVIDADES ACADÊMICAS
EMITIDO EM 18/03/2020 14:09

DECLARAÇÃO DE DISCIPLINAS MINISTRADAS

Declaramos para os devidos fins que o Docente VICTOR SCHMIDT COMITTI, Matrícula SIAPE de número 3082930, ministrou nesta instituição os seguintes componentes curriculares, em seus respectivos períodos letivos:

2019.1	**Nível**
EMPREENDEDORISMO - 40 h	TÉCNICO
GESTÃO DE PROJETOS - 40 h	GRADUAÇÃO
MATEMÁTICA FINANCEIRA - 40 h	GRADUAÇÃO
METODOLOGIA E TÉCNICAS DE PESQUISA - 40 h	GRADUAÇÃO
2019.2	**Nível**
CLIMATOLOGIA E METEOROLOGIA - 40 h	GRADUAÇÃO
FUNDAMENTOS DE ADMINISTRAÇÃO FINANCEIRA E CONTABILIDADE - 18 h	FORMAÇÃO COMPLEMENTAR
FUNDAMENTOS DE LOGÍSTICA - 18 h	FORMAÇÃO COMPLEMENTAR
INTRODUÇÃO À ÉTICA - 8 h	FORMAÇÃO COMPLEMENTAR
METODOLOGIA CIENTÍFICA I - 80 h	GRADUAÇÃO

Bom Sucesso, 18 de Março de 2020

Código de Verificação:
fc6ab7ee78

Para verificar a autenticidade deste documento acesse **http://sig.ifsudestemg.edu.br/sigaa/public/autenticidade/tipo_documento.jsf**, informando a Matrícula do SIAPE , data de emissão do documento e o código de verificação.

MINISTÉRIO DA EDUCAÇÃO
INSTITUTO FEDERAL DE EDUCAÇÃO, CIÊNCIA E TECNOLOGIA DO SUDESTE DE MINAS GERAIS

DECLARAÇÃO Nº 54 / 2020 - BSCSDENS (11.01.10.01.01)

Nº do Protocolo: 23223.001239/2020-30

Juiz de Fora-MG, 11 de Março de 2020

DECLARAÇÃO

Declaro para os devidos fins que VICTOR SCHMIDT COMITTI cumpriu o horário de atendimento docente descrito na tabela abaixo, referente ao segundo semestre de 2019, totalizando 4 horas semanais.

SEGUNDA	TERÇA	QUARTA	QUINTA	SEXTA
			16:00-18:20	9:20-11:00

(Assinado digitalmente em 11/03/2020 15:38)
PEDRO HENRIQUE DE OLIVEIRA E SILVA
COORDENADOR
Matrícula: 1758559

Para verificar a autenticidade deste documento entre em https://sig.ifsudestemg.edu.br/documentos/ informando seu número: **54**, ano: **2020**, tipo: **DECLARAÇÃO**, data de emissão: **11/03/2020** e o código de verificação: **549262f6ff**

DECLARAÇÃO

Declaro para os devidos fins que **Victor Schimitti Comitti** é o orientador do TCC do curso de Análise e Desenvolvimento de Sistemas dos alunos:

- SOLANGE PEREIRA DA SILVA
- RODRIGO MORAES DOS SANTOS PACHECO

Bom Sucesso, 18 de março de 2020

ASSINADO E/OU AUTENTICADO PELO PROFESSOR GRAZIANY THIAGO FONSECA
SIAPE 19669046

Coordenador do curso de Análise e Desenvolvimento de Sistemas

Elsevier Editorial System(tm) for
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Manuscript Draft

Manuscript Number: CSDA-D-19-00871

Title: Bayesian Dynamic Models for Count Data with Overdispersion and Inflation of Zeros

Article Type: Research Paper

Section/Category: II. Statistical Methodology for Data Analysis

Keywords: zero inflated/overdispersed distribution;
Negative binomial distribution;
Parameter driven model;
Dynamic generalized linear model;
Bayesian inference

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Corresponding Author's Institution: Instituto Federal Sudeste Minas Gerais

First Author: Victor Schmidt Comitti, Ph.D.

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Victor Schmidt Comitti

Instituto Federal Sudeste Minas Gerais

Rua Independência, 30 ,

Bom Sucesso, MG, Brazil

victorsch2@gmail.com

August 20, 2019

Dear Editor:

I am pleased to submit an original research article entitled *Bayesian Dynamic Models for Count Data with Overdispersion and Inflation of Zeros* for consideration by *Computational Statistics & Data Analysis.* This is an original work that is not in consideration for publication elsewhere.

In this paper we present several new methods for modeling count data time series when the use of a Poisson distribution based model is not appropriate. The new methods introduced in our manuscript include a general framework for uniparametric dynamic Bayesian models whose particular cases are the Bell, Poisson-Lindley, Borel and Yule-Symon distributions and a Dynamic Bayesian Negative Binomial Model (DBNBM). The inference of these models is based on the sequential procedure outlined by West, Harrison and Migon (1985) and includes numerical approximations when no closed-form solution is available for the updating steps. In the case of the DBNBM, we also propose a Bayesian estimator for the static shape parameter using Adaptative Rejection Metropolis Sampling. As far as we are aware, no work in the literature follows a similar approach. We also present a simulation study to evaluate the properties of this estimator along with two real life data applications that highlight situations in which our methods outperform the conventional Poisson DGLM.

Based on our results, we firmly believe that the framework developed in this manuscript is a viable alternative for modeling time series of counts in the presence of overdispersion or/and inflation of zeros. We also believe that this paper fits the scope of *Computational Statistics & Data Analysis* because of the applicability of the methods presented and the focus on time series analysis .

The authors have no conflicts of interest to disclose.

I kindly ask that all correspondence concerning this submission should be addressed to me

Thank you for your consideration!

Sincerely,

Victor Schmidt Comitti

Bayesian Dynamic Models for Count Data with Overdispersion and Inflation of Zeros

Victor Schmidt Comitti[1], Thiago Rezende dos Santos, Fabio Nogueira Demarqui

Universidade Federal de Minas Gerais
Institudo Federal Sudeste de Minas Gerais - Campus Bom Sucesso

Abstract

Most of the proposed dynamic parameter-driven models for count time series are based on the assumption of a Poisson distribution for the observations ignoring, sometimes, problems related to overdispersion and zero inflation in the data. The objective of this paper is to introduce novel dynamic Bayesian models for count time series to overcome this problem. A family of dynamic Bayesian uniparametric models for count data is introduced whose particular cases are the Bell, Poisson-Lindley, Yule-Simon and Borel models. Furthermore, a biparametric Dynamic Bayesian Negative Binomial model with unknown shape parameter is provided. The inferential procedure preserves the sequential analysis of the models and is similar to the Dynamic Generalized Linear Models (DGLM) with with the novelty of incorporating Monte Carlo integration to the recursive algorithm in order to deal with the intractability of the updating distributions and an ARMS step to sample from the posterior distribution of the shape parameter. The simulation results show a good performance of the estimator considered for the static parameter of the biparametric Negative binomial model which can be reasonably estimated. The application results also highlights a better performance of the proposed uni/biparametric models over the Poisson model.

Keywords: zero inflated/overdispersed distribution, Negative binomial distribution, Parameter driven model, Dynamic generalized linear model, Bayesian inference

1. Introduction

Time series of counts arise frequently in fields such as Finance, Economics, Hydrology, Epidemiology among others. Modeling of this kind of data, typically, can be done within one of two frameworks: the class of Observation Driven (OD) models and the class of Parameter Driven (PD) models. Let Y_t represent an observation from a time series in time t. An OD model can be written as:

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$$Y_t = f(D_{t-1}, \epsilon_t),$$

where D_{t-1} denotes the history of the process up to the $t-1$ observation and ϵ_t is a white noise. For OD models the parameters are dynamic but their evolution is deterministic and invariant over time given past information. Many models within the OD class rely on the Generalized Linear Models (GLM) theory of Nelder and Wedderburn (1972) [1] to extend the Box & Jenkins methods [2] to count data (Davis, Dunsmuir and Streett (2003 [3])). Others are based on the binomial thinning operator such as the integer-valued autoregressive (INAR) process introduced independently by McKenzie (1985) [4] and Al-Osh and Alzaid (1987) [5]. Some of them deal with the problem of conditional heterocedasticity (Ferland et al, 2006) [6] and inflation of zeros (Barreto-Souza, 2015) [7].

PD models have the following structure:

$$Y_t = f(\theta_{\mathbf{t}}, \nu_t)$$

$$\theta_t = g(\theta_{\mathbf{t-1}}, \eta_t),$$

again, ν_t and η_t are white noise processes and θ represents a state vector that evolves as a Markovian process. In a PD model the parameter evolution has an idiosyncratic error component that makes them non predictable even with the full information of the underlying process. PD models for counts belong to the wider class of state space models (SSM) (Durbin and Koopman, 2012) [8] under the classical and Bayesian perspectives. The autocorrelation and overdispersion of the observations are generally introduced into the modeling through a hidden process. Zeger (1988) [9] proposes a log linear classical model for counts in which a multiplicative stationary latent process ϵ_t captures the heterogeneity of the process. Conditionally on ϵ_t the sequence of observations Y_t has the same mean and variance but, marginally, it is overdispersed. The idea of using a latent process to introduce overdispersion and autocorrelation into a model has been further developed in several works like Brännäs and Johansson (1994) [10], Campbell (1994) [11], Chan and Ledolter (1995) [12] and Davis, Dunsmuir and Wang (2000) [13].

Harvey and Fernandes (1989) [14] introduce a PD model that assumes the counts to be drawn from a Poisson distribution whose mean μ_t has a prior distribution Gamma. Gamerman, Santos and Franco (2013) [15] propose yet another family of Non-Gaussian State Space Models (NGSSM) with exact marginal likelihood in which the dynamic Poisson model of Harvey & Fernandes is a particular case. Aktekin, Soyer and Xu (2013) [16] present a Bayesian Poisson dynamic model to assess mortgage default risk in the NGSSM family. After that, Aktekin, Polson, and Soyer (2018) [17] provide a Bayesian Poisson dynamic model for modeling multivariate count data and its sequential procedure. A good review about these models may be found in Soyer (2018) [18].

West, Harrison and Migon(1985) [19] use an approximated Bayesian approach to propose a much more general class of non-Gaussian and non-linear models. This wider class, named as Dynamic Generalized Linear Models (DGLM), extends the GLM formalism to time series in a Bayesian framework. The inference of these models often require the use of linear approximations since the analytical tractability of the updating steps can be easily lost.

For a more complete overview of these methods the reader may refer to West and Harrison (1997) [20] (chapter 13). Recent developments on the subject can be found in the works of da Silva, Migon and Correia (2011) [21], da Silva and da Silva (2017) [22] and Souza, Migon and Pereira (2018) [23].

In general, most of the proposed PD models for time series of counts assume a Poisson distribution for the observations. This is a limiting choice since the Poisson distribution is only adequate for modeling processes in which the mean and the variance are equal – a requirement that will not be met for many real life data sets. In the presence of overdispersion and/or inflation of zeros, alternative distributions such as the Bell or Poisson mixtures can be viable options since they are not bound to the equidispersion assumption.

The main goal of this paper is to introduce new models for discrete response time series under a Bayesian perspective. The methods presented here are related to the DGLM family of West, Harrison and Migon, but are not restricted to the Exponential Family (EF). In what follows, two lines of work are presented. In the first, we introduce a new general framework for uniparametric Bayesian dynamic count models. The proposed estimation procedure for these models includes the evolution and updating steps of the DGLM class but, since the use of conjugate priors is not possible most of the times, the analytic tractability of the results is lost. For this reason we incorporate Monte Carlo integration to the recursive inference algorithm in order to deal with the updating steps when no closed-form expressions are available for them. Under this new framework we are particularly interested in the following overdispersed/zero-inflated distributions: Bell, Poisson Lindley, Yule Simon and Borel – each of them has unique features that can make them more appealing than the Poisson in some particular situations.

In the second line of work we introduce a novel biparametric Dynamic Bayesian Negative Binomial Model (DBNBM) for modeling overdispersed time series. We consider that the main contributions of our proposal to the literature are: i) The observation equation of the DBNBM is parametrized in terms of the mean of the process (denoted by μ_t), in the same way as in the Negative Binomial GLM, thus improving the interpretability of the model; ii) a conjugate Beta Prime of the Second Kind prior distribution for μ_t is used, which allows the model to retain analytic tractability throughout the inference cycle; iii) an efficient scheme for estimating the static shape parameter of the model using Adaptative Rejection Metropolis Sampling (ARMS) is introduced. As far as the authors are aware, this method was not used in a similar context before.

This paper has the following structure: in Section 2 we present a general framework for Bayesian dynamic models for uniparametric distributions; in Section 3 we introduce the Dynamic Bayesian Negative Binomial Model; in Section 4 a simulation study is carried out; in Section 5 we provide applications to real count time series and a comparison between the models presented; Section 6 is left for the final remarks.

2. A General Framework for Dynamic Bayesian Uniparametric Models

The DGLM, introduced by West, Harrison and Migon (1985) [19], is a very general class of dynamic linear models. Its basic structure is very similar to that of the GLM class.

Generalized Linear Models apply to conditionally independent observations that belong to the EF. The main idea behind those models is to link the mean of the observations μ_t to a linear predictor of covariates using a suitable link function $g(.)$. In the DGLM theory the linear predictor is substituted by a space state model in order to incorporate the autocorrelation structure of a time series.

Many uniparametric discrete data distributions are not in the EF. Even those that are, like the Bell distribution, very often have conjugate prior distributions that are difficult to work with. Bayesian inference for these distributions are not exact and calls for intensive computational methods, like Monte Carlo Markov Chain (MCMC), in order to obtain a sample from the posterior distribution of the parameters. In the context of the DGLM class it is usually preferred, whenever possible, not to use intensive computational methods such as the MCMC in order to preserve the sequential nature of the Bayesian inference and to avoid lengthy computational times (see, for example, [21]). We propose here a general and simple framework based on the DGLM class for dealing with Dynamic Bayesian models when the observation equation is an uniparametric distribution. This setting preserves the sequence of evolution and updating steps of the DGLM inference but does require Bayesian conjugacy since the intractable integrals involved in the updating steps can be handled via Monte Carlo Integration (MCI). It is also not necessary that the observation equation belongs to the EF. Let y_t, $t = 1, 2, \cdots, T$ be a time series of counts, the proposed approach has the following basic structure:

- Observation equation:

  Any uniparametric count distribution with probability function $p(y_t \mid \mu_t)$ where $\mathbb{E}[y_t \mid \mu_t] = \mu_t$ and $\mu_t > 0$.

- Prior:

  Since the parameter μ_t is strictly positive any distribution with support in the interval $(0, \infty)$ may be appropriate. The Gamma distribution arises as natural choice due to its flexibility and ease in the elicitation of its moments.

- Link Function:

  There are several possible link functions. For the rest of this section we will assume a logarithmic one. The log-link is very suitable since it maps the strictly positive mean μ_t to the real line. It also provides closed-form expressions for some of the quantities that will be needed in the updating steps of the model. Thus, we can define:

$$g(\mu_t) = \log(\mu_t) = \mathbf{F}_t'\theta_t \tag{1}$$

- Evolution equation:

$$\boldsymbol{\theta}_t = \mathbf{G}_t\boldsymbol{\theta}_{t-1} + \boldsymbol{\omega}_t, \quad \omega_t \sim (0, \mathbf{W}_t). \tag{2}$$

- Initial Information:

$$(\boldsymbol{\theta}_0 \mid D_0) \sim (\mathbf{m}_0, \mathbf{C}_0). \tag{3}$$

In equations (1) and (2), $\boldsymbol{\theta}_t$ represents a $d \times 1$ state vector, $\mathbf{G_t}$ is a $d \times d$ evolution matrix and $\mathbf{F_t}$ is a $d \times 1$ design vector. The link function $g(.)$ is continuous, monotonic and strictly positive. The vector $\boldsymbol{\omega}_t$ denotes a sequence of independent and non correlated errors partially specified in terms of its first two moments with variance $\mathbf{W}_t$. Equation (3) provides the initial distribution for the hidden states and completes the specification of the model. Similarly to $\boldsymbol{\omega}_t$, the distribution of $\boldsymbol{\theta}_0$ conditional on the initial set of information D_0 is specified only by its first two moments $\mathbf{m}_0$ and $\mathbf{C}_0$.

The inference cycle follows the steps of evolution and updating presented in DGLM, West and Harrison (1997) [20]. Applying the evolution equation we obtain the priors for the state vector $\boldsymbol{\theta}_t$ and the linear predictor λ_t. That is,

$$(\boldsymbol{\theta}_t \mid D_{t-1}) \sim (\mathbf{a}_t, \mathbf{R}_t),$$

where $\mathbf{a}_t = \mathbf{G}_t\mathbf{m}_{t-1}$, $\mathbf{R}_t = \mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}_t' + \mathbf{W}_t$ and $(\lambda_t \mid D_{t-1}) \sim (f_t, q_t)$. Observe that, if $\mathbf{W}_t = 0$, then $\mathbb{VAR}[\boldsymbol{\theta}_t \mid D_{t-1}] = \mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}_t'$; that is: the model conveys no loss of information in the passage from $t-1$ to t. On the other hand, if $\mathbf{W}_t >> \mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}_t'$, the stochastic error dominates the evolution implying big loss of information in the state transition. One can interpret the values of the matrix $\mathbf{W}_t$ as a measure of information loss in the passage from one state to the next. West & Harrison (1997) [20] suggest to think of $\mathbf{W}_t$ as fraction of $\mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}_t'$. Under this assumption, we can write $\mathbf{W}_t = \frac{1-\delta}{\delta}\mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}_t'$, where $\delta \in (0, 1]$ is called the discount factor.

The hyperparameters α_t and β_t of the prior distribution can be elicited by matching the moments of the linear predictor with f_t and q_t as described in the DGLM Poisson example in West and Harrison (1997) [20]. If the prior is a Gamma distribution, we have $\alpha_t = \frac{1}{q_t}$ and $\beta_t = \frac{exp(-f_t)}{q_t}$. Using the first order approximations of the digamma and trigamma functions and with some algebra it is a simple exercise to show that $\alpha_t = \frac{exp(-f_t)+1}{q_t}$ and $\beta_t = \frac{exp(f_t)+1}{q_t}$.

The predictive distribution $p(y_t|D_{t-1})$ can be obtained marginally from the joint distribution $p(y_t, \mu_t \mid D_{t-1}) = p(y_t \mid \mu_t, D_{t-1})p(\mu_t \mid D_{t-1})$. That is:

$$p(y_t \mid D_{t-1}) = \int_0^\infty p(y_t \mid \mu_t, D_{t-1})p(\mu_t \mid D_{t-1})d\mu_t. \tag{4}$$

Now, we can write $p(y_t \mid \mu_t, D_{t-1})$ as product of two functions: the first entirely dependent on the observation y_t and the other dependent on y_t and μ_t, therefore:

$$p(y_t \mid \mu_t, D_{t-1}) = Z(y_t)f(\mu_t, y_t)$$

Then, rewriting (4) we have:

$$
\begin{aligned}
p(y_t \mid D_{t-1}) &= Z(y_t)\int_0^{\infty} f(\mu_t, y_t)p(\mu_t \mid D_{t-1})d\mu_t \\
&= Z(y_t)\mathbb{E}[f(\mu_t)]
\end{aligned} \tag{5}
$$

Since y_t is a known quantity we are left with the problem of evaluating the expected value of a function $f(\mu_t)$. In most cases, there is no closed form solution to $\mathbb{E}[f(\mu_t)]$. A simple approach to handle the problem is to draw samples from the prior $p(\mu_t \mid D_{t-1})$ and approximate Expression (5) using MCI. The posterior distribution for the dynamic mean μ_t can be found by direct application of the Bayes' theorem and is given by:

$$
p(\mu_t \mid D_t) = \frac{p(y_t \mid \mu_t)p(\mu_t \mid D_{t-1})}{p(y_t \mid D_{t-1})}.
$$

Following the DGLM approach, the posterior moments of the linear predictor λ_t can be calculated from the pair: $f_t^* = \mathbb{E}[g(\mu_t)|D_t)]$, $q_t^* = \mathbb{VAR}[g(\mu_t)|D_t)]$. Since $g(\mu_t) = log(\mu_t)$, we are interested in the following quantities:

$$
\begin{aligned}
\mathbb{E}[(g(\mu_t)^n|D_t] &= \int_0^{\infty} g(\mu_t)^n p(\mu_t \mid D_t)d\mu_t \\
&= \frac{Z(y_t)}{p(y_t \mid D_{t-1})}\int_0^{\infty} g(\mu_t)^n f(\mu_t)p(\mu_t \mid D_{t-1})d\mu_t \\
&= \frac{Z(y_t)}{p(y_t \mid D_{t-1})}\int_0^{\infty} h(\mu_t)p(\mu_t \mid D_{t-1})d\mu_t,
\end{aligned} \tag{6}
$$

where $n = 1, 2, \cdots$ and $h(\mu_t) = [g(\mu_t)]^n f(\mu_t)$. As before, it is possible to approximate (6) via MCI. As suggested by West and Harrison (1997) [20], updating of the partially specified state vector $\boldsymbol{\theta_t}$ can be accomplished via Linear Bayes Estimation (LBE). The posterior $(\boldsymbol{\theta}_t \mid D_t)$ is also specified in terms of the first two moments $\mathbf{m}_t$ and $\mathbf{C}_t$ with:

$$
\mathbf{m_t} = \mathbf{a_t} + \frac{1}{q_t}\mathbf{R_t}\mathbf{F_t}(f_t^* - f_t), \tag{7}
$$

$$
\mathbf{C_t} = \mathbf{R_t} - \frac{1}{q_t}\left[\mathbf{R_t}\mathbf{F_t}\mathbf{F_t}'\mathbf{R_t}\left(1 - \frac{q_t^*}{q_t}\right)\right]. \tag{8}
$$

The table below shows the expressions of $Z(y_t)$ and $f(\mu_t)$ for the particular uniparametric distributions described on this section.

Table 1: $f(\cdot)$ and $Z(\cdot)$ functions of the one-step-ahead predicted distribution for the observations according to each distribution.

Distribution	$Z(y_t)$	$f(\mu_t)$
Bell	$\frac{B_{y_t}}{y_t!}$	$exp(1-e^{W_0(\mu_t)})W_0(\mu_t)^{y_t}$
Borel shifted	$\frac{1}{(y_t+1)!}$	$exp\left(\frac{\mu_t}{\mu_t+1}(y_t+1)\right)\left(\frac{\mu_t}{1+\mu_t}(y_t+1)\right)^{y_t}$
Poisson-Lindley	1	$\frac{\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)^2\left(\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)+y_t+2\right)}{\left(\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)+1\right)^{y_t+3}}$
Yule-Simon shifted	1	$\frac{\mu_t+1}{\mu_t}B\left(y_t+1,\frac{2\mu_t+1}{\mu_t}\right)$

2.1. Particular uniparametric cases

2.1.1. Bell distribution

Castellares et al. (2018) [24] introduce the Bell distribution and an associated regression model. The Bell probability function for $\theta > 0$ is given by

$$p(y_t \mid \theta_t) = \frac{B_{y_t}}{y_t!}\theta_t^{y_t}\exp(-\exp(\theta_t)+1), \qquad y_t = 0,1,2,\cdots, \tag{9}$$

where B_{y_t} are the Bell number defined as $B_n = \frac{1}{e}\sum_{k=0}^{\infty}\frac{k^n}{k!}$. Notice that equation (9) belongs to the EF with $\eta_t = \log(\theta_t)$, $\tau_t = 1$, $c(y_t) = \frac{B_{y_t}}{y_t!}$ and $a(\eta_t) = \exp(\exp(\eta_t)) = \exp(\theta_t)$. Using properties of the Exponential Family it is easy to prove that:

$$\mathbb{E}[Y_t \mid \theta_t] = \theta_t e^{\theta_t},$$
$$\mathbb{VAR}[Y_t \mid \theta_t] = (1+\theta_t)\theta_t e^{\theta_t}.$$

Since θ_t is strictly positive, then $\mathbb{VAR}[Y_t \mid \theta_t] > \mathbb{E}[Y_t \mid \theta_t]$, that is, Bell is an uniparametric naturally overdispersed distribution. The conjugate prior of the Bell can be found according to the properties of the EF but the normalizing constant of the resulting distribution does not have a closed-form making it hard to work with.

On the context of regression models, usually the interest lies on the mean μ_t of the process. So, letting $\mu_t = \theta_t e^{\theta_t}$ it is possible to rewrite (9) as :

$$p(y_t \mid \mu_t) = \frac{B_{y_t}}{y_t!}exp(1-e^{W_0(\mu_t)})W_0(\mu_t)^{y_t}, \qquad y_t = 0,1,2,\cdots,T.$$

where $W_0(.)$ represents the Lambert function. In this new parametrization we have that $\mathbb{E}[y_t \mid \mu_t] = \mu_t$ and $\mathbb{VAR}[y_t \mid \mu_t] = \mu_t(1+W_0(\mu_t))$.

2.1.2. Borel Shifted distribution

The Borel uniparametric distribution for a discrete random variable X_t was proposed by Borel(1942) [25] in the context of branching process and queuing theory. A Borel random variable is distributed according to $p(x_t \mid \lambda_t) = \frac{\exp(-\lambda_t x_t)(\lambda_t x_t)^{x_t-1}}{x_t!}$, for $x_t = 1, 2, 3, \cdots$, T. As we are interested in stochastic processes that can take zero values, we assume that $Y_t = X_t - 1$ and $\lambda_t = \frac{\mu_t}{(1+\mu_t)}$. It is easy to prove that the distribution for Y_t is a Borel shifted and its probability density function can be expressed as:

$$p(y_t \mid \mu_t) = \frac{\exp\left(\frac{\mu_t}{\mu_t+1}(y_t+1)\right)\left(\frac{\mu_t}{1+\mu_t}(y_t+1)\right)^{y_t}}{(y_t+1)!}, \qquad y_t = 0, 1, 2, 3, \ldots, T. \tag{10}$$

where $\mu_t > 0$ represents the mean and $\frac{\mu_t}{(1+\mu_t)^2}$ the variance of Y_t. Since $\frac{\mathbb{VAR}[Y_t|\mu_t]}{\mathbb{E}[Y_t|\mu_t]} = (1+\mu_t)^2 > 1$ the Borel distribution is also overdispersed. Equation (10) is similar to the Modified Borel Tanner distribution proposed by Gómez-Déniz et al. (2017) [26].

It is also possible to show that the Borel distribution is zero inflated, that is: the proportion of zeros drawn from a Borel is larger than the same proportion drawn from a Poisson distribution. To demonstrate that, one can use the zero-inflated index (ZII) ($z_i = 1 + \frac{log(p_0)}{\mu_t}$, where p_0 is the probability of getting a zero value) proposed by Puig and Valero (2006) [27]. Direct application of the Index formula to the Borel distributions yields

$$z_i = 1 + \frac{1}{1+\mu_t} > 2$$

Any $z_i > 0$ indicates a distribution that produces more zeros than the Poisson. The Borel distribution has a ZII at least greater than two which is a distinctive feature among count data distributions and makes it a candidate for modelling datasets with high frequency of zeros.

2.1.3. Poisson-Lindley distribution

Another way to introduce overdispersion into a model is by using mixture Poisson distributions as the observation equation. These distributions arise when we allow the rate parameter μ_t of the Poisson to be a random variable following a distribution $G(\mu_t \mid \theta)$. If $G(\mu_t \mid \theta)$ is a Lindley distribution, the resulting mixture is the Poisson-Lindley (PLD) first presented by Sankaran (1970) [28]. Its probability function, for $\theta_t > 0$, is given by:

$$p(y_t \mid \theta_t) = \frac{\theta_t^2(\theta_t + y_t + 2)}{(\theta_t+1)^{y_t+3}},\ y_t = 0, 1, 2, \ldots;\ \theta_t > 0, \tag{11}$$

with mean and variance, respectively,

$$\mathbb{E}[Y_t \mid \theta_t] = \frac{\theta_t + 2}{\theta_t(\theta_t+1)} = \mu_t, \tag{12}$$

$$\mathbb{VAR}[Y_t \mid \theta_t] = \frac{\theta_t^3 + 4\theta_t^2 + 6\theta_t + 2}{\theta_t^2(\theta_t+1)}.$$

To verify that (11) is overdispersed notice that:

$$\frac{\mathbb{VAR}[Y_t \mid \theta_t]}{\mathbb{E}[Y_t \mid \theta_t]} = \frac{\theta_t^3 + 4\theta_t^2 + 6\theta_t + 2}{\theta_t(\theta_t + 2)}. \tag{13}$$

It is easy to see that, since θ_t is positive, the numerator in (13) is always greater than the denominator, thus making the Poisson Lindley distribution overdispersed. In fact, it is a simple calculus exercise to show that the equation (13) has a global minimum of, approximately, 4.33.

To parametrize the PLD in terms of the mean μ_t we solve (12) for θ_t to obtain $\theta_t = \frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}$. Then:

$$p(y_t|\mu_t) = \frac{\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)^2\left(\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)+y_t+2\right)}{\left(\left(\frac{\sqrt{\mu_t^2+6\mu_t+1}-\mu_t+1}{2\mu_t}\right)+1\right)^{y_t+3}}, \; y_t = 0,1,2,\cdots;\; \mu_t > 0, \tag{14}$$

with $\mathbb{E}[Y_t|\mu_t] = \mu_t$.

2.1.4. Yule-Simon shifted

Yule-Simon distribution (YSD) belongs to the broader class of Power Law distributions (see [29]). It is also, like the Poisson-Lindley, a mixture distribution. Suppose υ is a random variable following an exponential distribution of rate ρ_t, then a random variable U_t following a *Geometric*(e^{υ}) is Yule-Simon distributed with probability function:

$$p(U_t \mid \rho_t) = \rho_t B(U_t, \rho_t + 1), \qquad X_t = 1,2,3,\cdots,T, \rho_t > 0, \tag{15}$$

where $B(.)$ represents the Beta function. Now, defining $Y_t = U_t - 1$ we can shift (15) to obtain a modified YSD with support in the positive integers including zero, that is:

$$p(y_t \mid \rho_t) = \rho_t B(y_t + 1, \rho_t + 1), \qquad X_t = 0,1,2,3,\cdots,\rho_t > 0. \tag{16}$$

The first two central moments of (16) are given by:

$$\mathbb{E}[Y_t \mid \rho_t] = \frac{1}{\rho_t - 1}, \qquad \rho_t > 1$$

$$\mathbb{VAR}[Y_t \mid \rho_t] = \frac{\rho_t^2}{(\rho_t - 1)^2(\rho_t - 2)}, \qquad \rho_t > 2.$$

The ration between variance and mean can be easily calculated as:

$$\frac{\mathbb{VAR}[Y_t \mid \rho_t]}{\mathbb{E}[Y_t \mid \rho_t]} = \frac{\rho_t^2}{(\rho_t - 1)(\rho_t - 2)}, \qquad \rho_t > 2.$$

Note that, for $\rho_t > 2$, the above expression is always positive and decreases monotonically. Using L'Hopital theorem it is easy to demonstrate that $\lim_{\rho_t \to \infty} \frac{\mathbb{VAR}[Y_t|\rho_t]}{\mathbb{E}[Y_t|\rho_t]} = 1$. Therefore, the Yule-Simon Shifted distribution is overdispersed. Direct application of the ZII also shows inflation of zeros. Reparametrizing (16) in terms of $\mu_t = \frac{1}{\rho_t - 1}$ gives us:

$$p(y_t \mid \mu_t) = \frac{\mu_t + 1}{\mu_t} B\left(y_t + 1, \frac{2\mu_t + 1}{\mu_t}\right),$$

where, naturally, $E[Y_t|\mu_t] = \mu_t$.

3. A Biparametric Dynamic Bayesian Negative Binomial Model

In this section we present an approach for a Dynamic Bayesian Negative Binomial Model (DBNBM). The observation equation of this model is parametrized as in the Negative Binomial regression model from GLM and a prior conjugate distribution is assigned for the mean μ_t of the process. Let y_t, $t = 1, 2, \cdots, T$ be a time series of counts, the DBNBM is fully defined by the following equations:

- Observation equation:

$$p(y_t \mid \mu_t, \kappa) = \frac{\Gamma\left(y_t + k^{-1}\right)}{\Gamma(y_t + 1)\Gamma(\kappa^{-1})} \frac{(\kappa\mu_t)^{y_t}}{(1 + \kappa\mu_t)^{y_t + \kappa^{-1}}}. \tag{17}$$

  The Negative Binomial distribution has two parameters: the dynamic mean μ_t and a static parameter $\kappa > 0$ associated with the variance of the process. If the parameter κ is known, Equation (17) belongs to the Exponential family with $\phi_t = 1$, $\eta_t = log\left(\frac{\kappa}{1+\kappa\mu_t}\right)$, $c(y_t, \phi_t) = \frac{\Gamma\left(y_t + \kappa^{-1}\right)}{\Gamma(y_t+1)\Gamma(\kappa^{-1})}$. We can prove that $\mathbb{E}[y_t|\mu_t] = \mu_t$ and $\mathbb{VAR} = \mu_t + \kappa\mu_t$. Observe that the geometric distribution is a particular case of the Negative Binomial when $\kappa = 1$;

- Prior for μ_t:

$$p(\mu_t|\kappa, \alpha_t, \beta_t D_{t-1}) = \frac{\kappa^{\alpha_t}}{B(\alpha_t, \beta_t)} \frac{\mu_t^{\alpha_t - 1}}{(1 + \kappa\mu_t)^{\alpha_t + \beta_t}}. \tag{18}$$

  Equation (18) is a particular case of the Generalized Beta of the second kind (GB2K) distribution. The GB2K was chosen over, for example, a Gamma distribution, because it is the conjugate prior of the Negative Binomial distribution parametrized as in (17);

- Link Function:

$$g(\mu_t) = \log(\mu_t) = \mathbf{F_t}'\theta_t; \tag{19}$$

- Prior for κ:

$$p(\kappa \mid D_{t-1}) = \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa), \forall\ t \tag{20}$$

  where $r, s > 0$. The Gamma distribution is very flexible and this is the main reason why it was chosen as a prior for κ.

- Equations (2) and (3) complete the specification of the model.

3.1. Inference

The inference cycle for the DBNBM follows the same scheme of evolution and updating shown in the previous section for the uniparametric models. The prior distributions for the state vector $\boldsymbol{\theta}_t$ and the linear predictor λ_t can be derived by direct application of the system equation as already described. To evaluate the hyperparameters α_t and β_t in terms of f_t and q_t observe that:

$$f_t = \mathbb{E}[\log(\mu_t) \mid \kappa, \alpha_t, \beta_t D_{t-1}] = \psi(\alpha_t) - \psi(\beta_t) - log(\kappa), \tag{21}$$

$$q_t = \mathbb{VAR}[\log(\mu_t) \mid \alpha_t, \beta_t, \kappa, D_{t-1}] = \psi'(\alpha_t) + \psi'(\beta_t). \tag{22}$$

The proof of the expressions above is presented in the Appendix A. Again, using first order approximations for the Digamma and Trigamma functions we can solve (21) and (22) for α_t and β_t to obtain:

$$\alpha_t \approx \frac{1 + \kappa exp(f_t)}{q_t},$$
$$\beta_t \approx \frac{exp(-f_t) + \kappa}{q_t \kappa}.$$

The predictive can be obtained marginally, as before, from the joint distribution $p(y_t, \mu_t, \kappa \mid D_{t-1}) = p(y_t \mid \mu_t, \kappa, D_{t-1}) p(\mu \mid \kappa, D_{t-1}) p(\kappa \mid D_{t-1})$ following the steps below:

$$\begin{aligned} p(y_t \mid D_{t-1}) &= \int_0^\infty \int_0^\infty p(y_t \mid \mu_t, \kappa, D_{t-1}) p(\mu_t \mid \kappa, D_{t-1}) p(\kappa \mid D_{t-1}) d\mu_t d\kappa \\ &= \int_0^\infty \frac{1}{B(\alpha_t, \beta_t)} \frac{\Gamma\left(y_t + k^{-1}\right)}{\Gamma(y_t + 1)\Gamma(\kappa^{-1})} B(\alpha_t + y_t, \beta_t + \kappa^{-1}) \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa \end{aligned} \tag{23}$$

Now, observe that, even though (23) is correct, it may not be a convenient expression from a computational point of view. This is because in most software there is a superior limit for the Gamma function. In R, for instance, this limit is 171 so that any observation with value equal or larger than this threshold would cause a numerical error in the estimation algorithm. To overcome this problem we chose to work with the Beta function instead of the Gamma. So, we rewrite the gamma function from (23) in terms of the Beta function defined as: $B(a,b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$ for $a, b \in \mathbb{R}^+$ and use the recurrence relation $B(y_t, \kappa^{-1}) = B(y_t+1, \kappa^{-1})\frac{y_t+\kappa^{-1}}{y_t}$. So, plugging this expressions into (23) we obtain

$$p(y_t \mid D_{t-1}) = \int_0^\infty \frac{1}{B(\alpha_t,\beta_t)} \frac{1}{y_t+\kappa^{-1}} \frac{B(\alpha_t+y_t, \beta_t+\kappa^{-1})}{B(y_t+1,\kappa^{-1})} \frac{s^r}{\Gamma(r)}\kappa^{r-1}\exp(-s\kappa)d\kappa$$

Integral (3.1) does not have an analytic solution. Da Silva and Migon (2011) [21] use numerical integration to handle a similar problem when working on a Dynamic Bayesian Beta Model. We found, however, that this approach is very prone to numerical errors when we are dealing with count data. Since it is very easy to sample from a Gamma distribution with parameters r and s, we chose, instead, to approximate equation (3.1) using MCI, like in section 2. MCI, in this situation, can work as an efficient tool at a lower computational cost in relation to MCMC methods.

The one-step ahead forest $\hat{y}_t = E[y_t \mid D_{t-1}, \kappa]$ can be obtained by direct application of the law of total expectations according to the following sequence of steps:

$$\begin{aligned}
\mathbb{E}[y_t \mid D_{t-1}] &= \mathbb{E}[\mathbb{E}[\mathbb{E}[y_t \mid \mu_t, \kappa]] \mid D_{t-1}] \\
&= \mathbb{E}[\mathbb{E}[\mu_t \mid \kappa] \mid D_{t-1}] \\
&= \mathbb{E}\left[\frac{\alpha_t(\kappa)}{\kappa(\beta_t(\kappa)-1)} \mid D_{t-1}\right]. \qquad (24)
\end{aligned}$$

Since the hyperparameters α_t and β_t are both functions of κ, there is no exact solution to Equation (24), although we can approximate the expression by means of the usual Monte Carlo methods.

Given a new observation y_t, we can update the dynamic parameter μ_t using the Bayes' Theorem.

$$p(\mu_t, \kappa \mid D_t) = \frac{p(y_t \mid \mu_t, \kappa, D_{t-1})p(\mu_t \mid \kappa, D_{t-1})p(\kappa \mid D_{t-1})}{p(y_t \mid D_{t-1})}.$$

Then, integrating κ out

$$\begin{aligned}
p(\mu_t|D_t) &= \frac{\int_0^\infty p(y_t \mid \mu_t, \kappa, D_{t-1})p(\mu_t \mid \kappa, D_{t-1})p(\kappa \mid D_{t-1})d\kappa}{p(y_t \mid D_{t-1})} \\
&= \frac{1}{p(y_t \mid D_{t-1})B(\alpha_t,\beta_t)} \int_0^\infty \frac{(y_t+\kappa^{-1})^{-1}}{B(y_t+1,\kappa^{-1})} \frac{\kappa^{\alpha_t+y_t}\mu_t^{\alpha_t+y_t-1}}{(1+\kappa\mu_t)^{y_t+\kappa^{-1}+\alpha_t+\beta_t}} \frac{s^r\kappa^{r-1}exp(-s\kappa)}{\Gamma(r)}d\kappa \qquad (25)
\end{aligned}$$

Based on Equation (25) the n-th moment of the linear predictor can be found from:

$$\mathbb{E}[\log(\mu_t^n \mid D_t)] = \int_0^\infty \log^n(\mu_t)p(\mu_t \mid D_t)d\mu_t.$$

Then, for $n = 1$ and $n = 2$ we have, respectively:

$$\mathbb{E}[\log(\mu_t) \mid D_t) = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty \frac{1}{y_t + \kappa^{-1}} \frac{1}{B(y_t + 1, \kappa^{-1})} \frac{B(\alpha_t + y_t, \beta_t + \kappa^{-1})}{B(\alpha_t, \beta_t)}$$
$$\times \left[\psi(\alpha_t + y_t) - \psi(\beta_t + \kappa^{-1}) - log(\kappa)\right] \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa, \tag{26}$$

$$\mathbb{E}[\log^2(\mu_t) \mid D_t] = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty \frac{1}{y_t + \kappa^{-1}} \frac{1}{B(y_t + 1, \kappa^{-1})} \frac{B(\alpha_t + y_t, \beta_t + \kappa^{-1})}{B(\alpha_t, \beta_t)}$$
$$\times \left[(\psi(\alpha_t + y_t) - \psi(\beta_t + \kappa^{-1}) - log(\kappa))^2 + \psi'(\alpha_t + y_t) + \psi^{'}(\beta_t + \kappa^{-1})\right]$$
$$\times \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa. \tag{27}$$

The proof of results (26) and (27) is displayed in Appendix B. Notice that both equations can be decomposed into a function of κ times the kernel of a Gamma distribution. Thus, it is easy to approximate the integrals via MCI techniques. Therefore, using the results above, $f_t^* = \mathbb{E}(\lambda_t \mid D_t) = \mathbb{E}[\log(\mu_t) \mid D_t)$ and $q_t^* = \mathbb{VAR}(\lambda_t \mid D_t) = \mathbb{E}[\log^2(\mu_t) \mid D_t] - f_t^{*2}$. As usual, we can employ equations (7) and (8) to update the state vector via Linear Bayes Estimation. Finally, the posterior distribution for the static parameter κ considering the whole information set D_T is given by:

$$p(\kappa|D_T) = \frac{\left[\prod_{t=1}^T p(y_t \mid D_{t-1}, \kappa)\right] p(\kappa \mid D_{t-1})}{\int_0^\infty \left[\prod_{t=1}^T p(y_t \mid D_{t-1}, \kappa)\right] p(\kappa \mid D_{t-1}) d\kappa}, \tag{28}$$

where $p(y_t \mid D_{t-1}, \kappa) = \int_0^\infty p(y_t \mid \mu_t, D_{t-1}) p(\mu_t \mid D_{t-1}) d\mu_t = \frac{1}{B(\alpha_t, \beta_t)} \frac{1}{y_t + \kappa^{-1}} \frac{B(\alpha_t + y_t, \beta_t + \kappa^{-1})}{B(y_t + 1, \kappa^{-1})}$.

Under quadratic loss the optimal predictor for κ is the posterior expected value, that is: $\hat{\kappa} = \mathbb{E}[\kappa \mid D_T] = \int_0^\infty \kappa p(\kappa \mid D_T) d\kappa$. Direct integration is not possible, tough, because there is no closed-form solution for the marginal posterior distribution above. In this work we chose to sample from the posterior distribution using the Adaptative Rejection Metropolis Sampling (ARMS) technique proposed by Gilks and Best (1995) [30]. The ARMS algorithm is a powerful and computationally efficient method to sample from uniparametric distributions. The samples obtained can be used straightforwardly for the computation of point estimates and credible intervals for the parameter κ.

3.2. Simulation Experiment

To evaluate Bayesian estimator for κ we carried out a Monte Carlo experiment. Four scenarios were designed with true parameter values $\kappa = 0.3$, $\kappa = 0.5$, $\kappa = 0.8$ and $\kappa = 1$. For each of these scenarios $L = 1000$ Monte Carlo replication of size $n = 50$, $n = 100$, $n = 200$

and $n = 300$ were generated from a Negative Binomial Local Level Model (LLM) with static variance $W = 0.02$.

The ARMS algorithm was implemented using the function of the same name contained in the 'dlm' package from R [31]. The application of the algorithm requires a bounded convex set for the target density. This is not the case here since equation (28) has support on $\mathbb{R}^+$. In these situations, the authors of the package suggest to restrict the support to a bounded set of probability close to one. In all scenarios studied in this work the true value of the parameter κ does not exceed one, so we chose to restrict the support for the target density in the interval $[0, 5]$. For the Bayesian inference chains of size 2000 were generated from which the first 1000 samples were discarded. Preliminary tests using diagnostic tools available on the 'coda' package [32] from R showed that a burn in of 1000 is enough to obtain stationary chains. We also could not detect any signs of auto-correlation in the chains, thus there was no need to use a lag. The prior distribution for κ was assumed to be a $Ga(1, 1)$. The reason for this choice is that we opted to give more weight to smaller values of κ since values much larger than one would imply a very overdispersed and non-realistic dataset. Two Bayesian Estimators were considered: the posterior median (BE-Median) and the posterior mean (BE-mean). We observed superior performance for the latter estimator and for this reason only Be-mean will be reported along with a 95% credible interval (CI) and an empirical coverage probability (CP).

The Bayesian Estimator for κ was evaluated according to its relative bias (RB) and Root of the Mean Squared Error (RMSE). A summary of the Monte Carlo study is presented on table (2). The BE-mean column reports the sample average of the 1000 estimates obtained for κ along with the mean RB defined, in percentage, as: $RB = \sum_{i=1}^{L} \frac{100(\hat{\kappa}_i - \kappa)}{|\kappa|}$, where $\hat{\kappa}_i$ denotes the estimate for κ obtained in the i-th Monte Carlo sample. The CI column indicates the 95% credibility interval associated with the point estimate and also the corresponding coverage probability (CP). In the last column the RMSE, defined as $RMSE = \sqrt{\frac{\sum_{i=1}^{L}(\hat{\kappa}_i - \kappa)^2}{L}}$ is presented.

The results show that the Bayesian estimator seems to be heavily influenced by the prior distribution chosen for the parameter. As expected, larger biases are observed for small values of true κ since the probability mass of the prior is concentrated around one. It is noteworthy, however, that as the sample size increases, the biases get progressive smaller, suggesting good behaviour of the Bayesian estimator for large data sets even when the prior distribution for the static parameter is distant from the target. When we have true $\kappa = 0.8$ or $\kappa = 1.0$, the biases are smaller than 5% regardless of samples size indicating that, if the choice of the prior distribution is close enough to the real value of the parameter, the Bayesian Estimator is well behaved even for small samples. As expected, the variance decreases for larger samples, as can be observed by the credible intervals. The coverage probabilities are all very close to the fixed nominal level of 95%, further confirming the good performance of the Bayesian estimator.

True parameter	Size	BE Mean (RB%)	CI (CP)	RMSE
$\kappa = 0.3$	50	0.373 (24.196)	[0.074, 1.112] (0.968)	0.288
	100	0.346 (15.185)	[0.102, 0.890] (0.952)	0.245
	200	0.326 (8.709)	[0.128, 0.732] (0.928)	0.206
	300	0.310 (3.377)	[0.134, 0.657] (0.928)	0.191
$\kappa = 0.5$	50	0.555 (10.912)	[0.16, 1.432] (0.957)	0.228
	100	0.521 (4.178)	[0.218, 1.117] (0.949)	0.235
	200	0.523 (4.530)	[0.258, 0.989] (0.946)	0.220
	300	0.519 (3.828)	[0.278, 0.945] (0.959)	0.212
$\kappa = 0.8$	50	0.828 (3.527)	[0.311, 1.868] (0.96)	0.337
	100	0.821 (2.652)	[0.393, 1.585] (0.958)	0.292
	200	0.822 (2.698)	[0.458, 1.434] (0.941)	0.257
	300	0.833 (4.146)	[0.493, 1.386] (0.945)	0.245
$\kappa = 1.0$	50	0.994 (-0.646)	[0.409, 2.112] (0.969)	0.379
	100	1.017 (1.696)	[0.525, 1.870] (0.954)	0.337
	200	1.022 (2.162)	[0.612, 1.666] (0.943)	0.281
	300	1.013 (1.267)	[0.639, 1.598] (0.937)	0.266

Table 2: Summary of the Monte Carlo study

4. Real Data Application

In this Section, we present two applications of the models developed in this work to real count time series. The data sets were chosen because of their idiosyncratic features: they both display overdispersion and inflation of zeros. The objective here is to show scenarios where the traditional Poisson DGLM may not be the most appropriate modeling choice. To compare between different models we are going to use the following metrics: the Bayes Factor and the Bayesian Information Criterion (BIC) to evaluate in sample performance and the one-step-ahead prediction accuracy to evaluate out of sample performance. In both applications, the MCI steps were carried out with samples of size 5000. Specifically for the DBNBM, the estimation of the static shape parameter was performed via ARMS as already shown in the previous section. A Gamma(1,1) prior was chosen for κ and single chains of sizes 5000 with a burn-in of 1.000 were generated from the posterior distribution (28). Point and interval estimates were calculated straightforwardly from these chains.

4.1. Skin Lesions Data

The skin lesions time series consists of the total number of skin lesions on bovines reported monthly to animal health laboratories in New Zealand from January 2003 until December 2009. This data set was first analyzed by Jazi et al (2011) [33] in the context of zero-inflated count data models. Figure (1) shows the behaviour of the time series. The time series plot shows no discernible trend or seasonality components; therefore, a LLM seems to be a good choice for modeling the data. The sample mean and variance of the data are, respectively, 1.4286 and 3.3563. Since the variance is more than twice as big as the mean, there is evidence that the skin lesion time series is overdispersed.

We fitted the uniparametric models of Section 2 and the DBNBM to the skin lesions data set. According to the dynamic models literature, values for the discount factor δ, typically, range from 0.8 to 1 (see West & Harrison, 1997 [20]) since, in structural models, the information loss is expected to increase smoothly from one state to the next. Observe that small values for δ would cause the stochastic term to dominate the system equation meaning that there is almost no flow of information between the states. For this reason we used $\delta = \{0.80, 0.85, 0.90, 0.95, 0.99\}$ in all the following analysis. Table 3, below, compares all the fitted models in terms of in-sample and out-of-sample performance:

Values in bold indicate the model with best performance according to each of the metrics evaluated. Looking at the table, we notice that the Poisson DGLM is superior to its uniparametric competitors in forecast accuracy when we consider the MSE as the main criterion of comparison. According to the MAE criterion, however, the forecasting accuracy of the Poisson DGLM is very similar to that of the Bell and Poisson-Lindley dynamic models. As for the in-sample performance, the BIC values suggest that, in this example, the Bell Dynamic Model specified with high discount factors is superior to the other uniparametric models. The Bayes factor also shows strong evidence in favor of the Bell and Poisson-Lindley models against the usual Poisson DGLM for $\delta = 0.99$ and $\delta = 0.95$. Compared to the other models, the Yule-Simon shifted and Borel shifted dynamic models have worse in sample performance according to the BIC, but similar out-of-sample performance when we consider the MAE.

Model	δ	**Estimated** κ **(95% CI)**	**MSE**	**MAE**	**BIC**	**BF**
Poisson	0.99	-	3.763	1.333	343.580	1
	0.95	-	3.750	1.345	340.591	1
	0.90	-	3.715	1.346	337.693	1
	0.85	-	3.697	1.341	342.266	1
	0.80	-	3.822	1.359	412.868	1
Borel	0.99	-	4.333	1.379	351.533	0.0187
	0.95	-	4.306	1.378	354.963	8.00e-04
	0.90	-	4.287	1.372	368.220	2.35e-07
	0.85	-	4.306	1.364	413.794	2.94e-16
	0.80	-	4.479	1.373	620.345	8.85e-46
Bell	0.99	-	3.977	1.349	326.679	4.68e+03
	0.95	-	3.969	1.354	329.002	3.29e+02
	0.90	-	3.916	1.345	333.868	6.771e+00
	0.85	-	3.919	1.340	359.881	1.00e-04
	0.80	-	3.989	1.332	462.387	1.77e-11
Poisson-Lindley	0.99	-	4.054	1.353	328.018	2.39e+03
	0.95	-	4.033	1.353	330.469	1.58e+02
	0.90	-	3.979	1.347	334.233	5.64e+00
	0.85	-	3.961	1.335	361.075	8.24e-05
	0.80	-	4.096	1.331	501.690	5.16e-20
Yule-Simon	0.99	-	4.048	1.332	334.845	78.825
	0.95	-	4.183	1.349	345.285	0.096
	0.90	-	4.264	1.356	357.057	6.24e-05
	0.85	-	4.300	1.354	366.244	6.21e-06
	0.80	-	4.286	1.341	373.307	3.896e+08
Negative Binomial	0.99	0.9701 (0.455, 1.694)	**3.488**	**1.394**	290	7.655e+11
	0.95	0.9119 (0.3975, 1.6313)	3.502	1.407	290.3	**4.015e+12**
	0.90	0.8277 (0.3066, 1.5685)	3.544	1.43	290.9	1.302e+11
	0.85	0.7211 (0.2006, 1.4601)	3.633	1.474	291.5	9.467e+11
	0.80	0.5821 (0.08824, 1.3326)	3.777	1.53	292.4	1.291e+27

Table 3: Performance summary of the proposed models applied to the skin Lesions data.

Table (3) also reports the results obtained using the DBNBM. Point estimates for κ are displayed along with a 95% credibility Interval. In a GLM context it is a well known fact that the presence of a dispersion parameter adds flexibility to the Negative Binomial Regression Model with respect to its Poisson counterpart. The same effect can be observed here: the DBNBM has a better in-sample performance compared to the Poisson DGLM according to the BIC and BF criteria and better out-of-sample performance according to the MSE. Comparison with the other dynamic uniparametric models also favors the DBNBMaccording to all criteria evaluated.

Figure 1 provides the one-step-ahead prediction for the skin lesions data set using the DBNBM. The gray shaded area represents the 95% percentile forecast credibility interval. For this illustration we used $\delta = 0.95$.

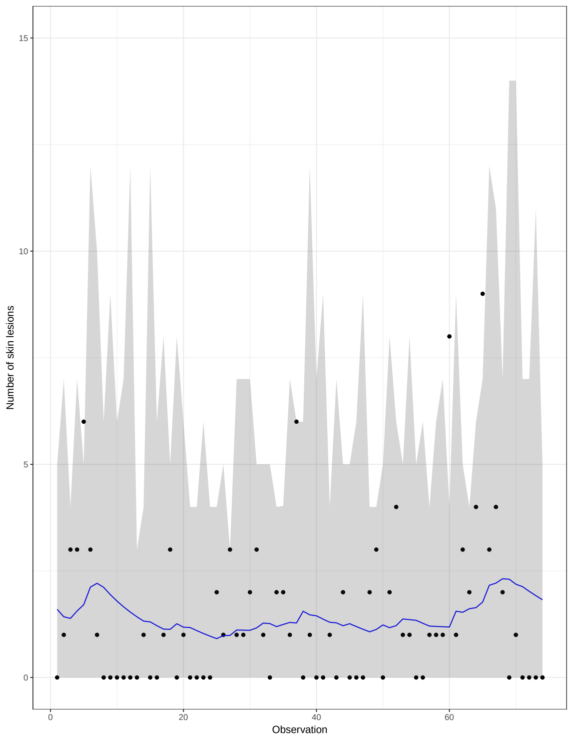

Figure 1: DBNBM: One-step-ahead prediction for the skin lesions data set. Solid line: predictions from the NBDM using $\delta = 0.95$; Gray Area: approximate 95% credibility interval.

4.2. Syphilis Data

The Syphilis Data data set consists of the weekly number of Syphilis cases reported in Porto Rico from 2007 until 2010, totaling 209 observations. This data is available from the ZIM package in R [34] and its primary source is the Center of Disease Control of the United States (CDC). Figure (2) shows the time series plot. Likewise the skin lesions data set, there is no visual evidences of trend or seasonality. The sample mean and variance are 2.632 and 9.772, respectively, indicating the presence of overdispersion. An inspection of the histogram reveals a very high frequency of zeros suggesting that zero-inflated models, such as the Borel shifted or Yule-Simon shifted, could be adequate to model the data. As before, we fitted the uniparametric dynamic models and the DBNBM to the Syphilis time series using discount factors ranging from 0.99 to 0.80. In all cases a LLM was used. A summary of the results obtained is displayed on Table (4). Again, values in bold emphasize the model with the best performance in that particular criterion.

Model	δ	**Estimated κ (95% CI)**	**MSE**	**MAE**	**BIC**	**BF**
Poisson	0.99	-	10.31	2.467	1235.195	1
	0.95	-	10.42	2.499	1222.145	1
	0.90	-	10.69	2.532	1214.512	1
	0.85	-	11.00	2.567	1208.582	1
	0.80	-	11.34	2.607	1204.152	1
Borel	0.99	-	12.85	2.455	1024.745	4.995e+45
	0.95	-	12.80	2.457	1027.090	2.269e+42
	0.90	-	12.83	2.466	1036.586	4.328e+38
	0.85	-	12.86	2.476	1048.949	4.612e+34
	0.80	-	12.95	2.485	1071.177	7.504e+28
Bell	0.99	-	10.87	2.439	1016.298	3.411e+47
	0.95	-	10.89	2.460	1009.269	1.681e+46
	0.90	-	11.10	2.482	1011.627	1.137e+44
	0.85	-	11.36	2.511	1017.533	3.061e+41
	0.80	-	11.64	2.535	1027.079	2.824e+38
Poisson-Lindley	0.99	-	11.25	**2.436**	988.090	4.552e+53
	0.95	-	11.25	2.448	984.8453	3.38e+51
	0.90	-	11.38	2.470	987.3465	2.13e+49
	0.85	-	11.58	2.485	997.654	6.346e+45
	0.80	-	11.85	2.506	1013.0343	3.168e+41
Yule-Simon	0.99	-	12.02	2.449	1035.641	2.151e+43
	0.95	-	13.05	2.472	1075.841	5.883e+31
	0.90	-	13.35	2.490	1101.480	3.503e+24
	0.85	-	13.49	2.498	1121.530	8.004e+18
	0.80	-	13.62	2.506	1144.144	1.073e+13
Negative Binomial	0.99	1.58 (1.165, 2.082)	**10.03**	2.574	**927.2**	**1.045e+68**
	0.95	1.603 (1.175, 2.118)	10.40	2.653	930.3	3.478e+64
	0.90	1.63 (1.181, 2.165)	10.93	2.742	935.2	6.746e+61
	0.85	1.651 (1.185, 2.222)	11.66	2.855	940.3	2.511e+59
	0.80	1.661 (1.177, 2.256)	12.77	3.007	945.9	1.700e+57

Table 4: Performance summary of the proposed models applied to the Syphilis data.

Considering the majority of the metrics used, the Poisson DGLM is outperformed by all other models fitted to the data. The Bayes Factor, specially, shows strong evidence in favor of the alternative uniparametric dynamic models. By the MAE and BIC criteria, the

Poisson-Lindley Model with $\delta = 0.99$ is the uniparametric model that best fits the Syphilis time series. Results for the DBNBM also highlight a better overall performance over the Poisson DGLM. From table (4), it is also noteworthy that the point estimates for κ are larger than 1.6 for all values of discount factor used, thus indicating that this specific data set is highly overdispersed which explains the superiority of the other models. Figure 2 shows the one-step-ahead prediction along with 95% credibility intervals for the the syphilis time series with $\delta = 0.99$.

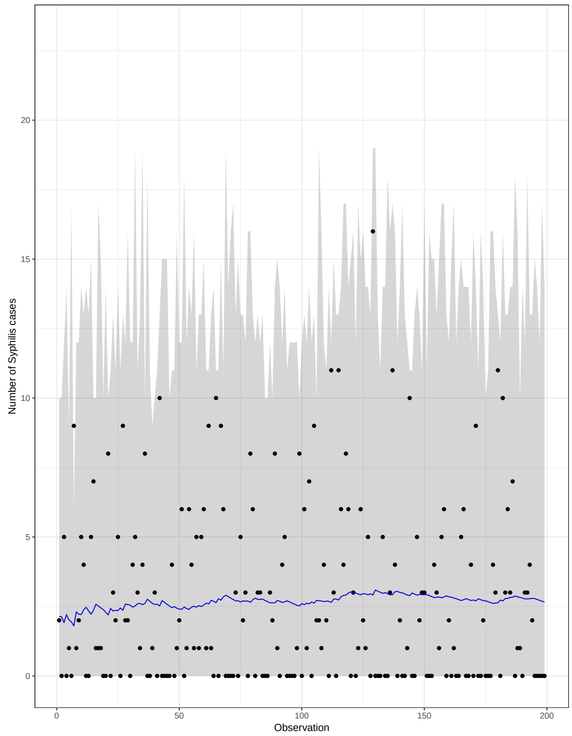

Figure 2: One-step-ahead prediction for the syphilis data set. Solid line: predictions from the DBNBM using $\delta = 0.99$; Gray Area: approximate 95% credibility interval.

5. Discussion and Final Remarks

Time series of count data can often exhibit characteristics such as overdispersion or inflation of zeros. In these situations, dynamic models based on the Poisson distribution may not be appropriate because they require the mean and the variance of the data to be equal. In this chapter we presented several alternatives to the Poisson DGLM for dealing with single time series of counts based on distributions that can more adequately capture these aspects in a data set. The main contributions of this work are the development of: 1) a general method of inference for Bayesian Dynamic Models that is suited for uniparametric distributions; 2) the introduction of a framework for a Dynamic Bayesian Negative Binomial Model. The inference procedures of the models presented here follows a Bayesian structure that resembles the DGLM framework, but is not restricted to distributions within the EF.

To keep the sequential nature of the Bayesian inference, some approximations such as Linear Bayes Estimation and Monte Carlo Integration, were used whenever the exact results were not available.

An important aspect concerning the DBNBM is the estimation of the static shape parameter κ. In the context of DGLM, it is well known that the estimation of the shape parameter when the observation equation is biparametric usually presents complications. Here, we present a Bayesian approach for the estimation of this parameter. In our proposal, κ is considered an unknown quantity following a Gamma prior distribution and the estimation is carried out via Adaptative Rejection Metropolis Sampling. An extensive simulation study was conducted and showed that the performance of the estimator is good for large samples even that the results are sensitive to the prior specification. The proposed models were also applied to two real data sets and compared to the Poisson DGLM in both in-sample and out-of-sample performance. Results showed clear superiority of the DBNBM over the Poisson Model in both examples. The uniparametric models, on the other hand, provided a competitive performance in the first data set and outperformed the DGLM Poisson in the second one.

Overall, the class of Bayesian dynamic models is very flexible since its structure allow for trend and seasonality components and intervention analysis. Covariates can also be included in the model by means of the F_t design matrix in the observation equation. The methods presented here are very general and can be extended, with a few modifications, to positive asymmetric data. A procedure similar to the one described for the DBNBM could be easily applied to the Gamma and Weibull distributions for example.

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Appendix A. Proof of results (21) and (22)

Result (21) :

$$\mathbb{E}[log(\mu_t) \mid \kappa, D_{t-1}] = \psi(\alpha_t) - \psi(\beta_t) - log(\kappa)$$

Proof. Let X be a Beta Prime random variable with parameters α_t e β_t, that is:

$$p(X \mid \alpha_t, \beta_t) = \frac{1}{B(\alpha_t, \beta_t)} \frac{X^{\alpha_t - 1}}{(1+X)^{\alpha_t + \beta_t}}$$

Now define $\mu_t = \frac{X}{\kappa}$. By the Jacobian transformation μ_t has the following distribution:

$$\begin{aligned} p(\mu_t|\kappa, \alpha_t, \beta_t) &= \frac{1}{B(\alpha_t, \beta_t)} \frac{(\kappa\mu_t)^{\alpha_t - 1}}{(1+\kappa\mu_t)^{\alpha_t + \beta_t}} \kappa \\ &= \frac{\kappa^{\mu_t}}{B(\alpha_t, \beta_t)} \frac{\mu_t^{\alpha_t - 1}}{(1+\kappa\mu_t)^{\alpha_t + \beta_t}} \end{aligned}$$

Therefore μ_t is distributed according to a generalized Beta of the second kind.

$$\begin{aligned}\mathbb{E}[log(\mu_t|\kappa,\alpha_t,\beta_t)] = \mathbb{E}\left[log\left(\frac{X}{\kappa}\right)|\alpha_t,\beta_t\right] &= \mathbb{E}[log(X)] - \mathbb{E}[log(\kappa)] \\ &= \psi(\alpha_t) - \psi(\beta_t) - log(\kappa)\end{aligned}$$

□

Result (22) :

$$\mathbb{VAR}[log(\mu_t) \mid \alpha_t,\beta_t,\kappa] = \psi'(\alpha_t) + \psi'(\beta_t)$$

Proof.

$$\begin{aligned}var[log(\mu_t) \mid \alpha_t,\beta_t,\kappa] &= var[log(X\kappa^{-1}) \mid \alpha_t,\beta_t] \\ &= var[log(X) \mid \alpha_t,\beta_t] \\ &= \psi'(\alpha_t) + \psi'(\beta_t)\end{aligned}$$

□

Appendix B. Demonstration of expressions (26) and (27)

Result (26):

$$\begin{aligned}\mathbb{E}[log(\mu_t) \mid D_t) = &\frac{1}{p(y_t \mid D_{t-1})}\int_0^\infty \frac{1}{y_t+\kappa^{-1}}\frac{1}{B(y_t+1,\kappa^{-1})}\frac{B(\alpha_t+y_t,\beta_t+\kappa^{-1})}{B(\alpha_t,\beta_t)} \\ &\times\left[\psi(\alpha_t+y_t) - \psi(\beta_t+\kappa^{-1}) - log(\kappa)\right]\frac{s^r}{\Gamma(r)}\kappa^{r-1}exp(-s\kappa)d\kappa.\end{aligned}$$

Proof. Using the posterior distribution for μ_t it is possible to write:

$$\mathbb{E}[log(\mu_t \mid D_t) = \frac{1}{p(y_t \mid D_{t-1})}\int_0^\infty log(\mu_t)\int_0^\infty \frac{(y_t+\kappa^{-1})^{-1}}{B(y_t+1,\kappa^{-1})}\frac{\kappa^{\alpha_t+y_t}}{B(\alpha_t,\beta_t)}\frac{\mu_t^{\alpha_t+y_t-1}}{(1+\kappa\mu_t)^{y_t+\kappa^{-1}+\alpha_t+\beta_t}}\frac{s^r}{\Gamma(r)}\kappa^{r-1}exp(-s\kappa)d\kappa d\mu_t$$

Notice that it is possible to invoke Fubini's Theorem to invert the order of integration on the expression above. This procedure will allow the integration over μ_t to be performed. This yields:

$$\mathbb{E}[log(\mu_t \mid D_t) = \frac{1}{p(y_t \mid D_{t-1})}\int_0^\infty \frac{(y_t+\kappa^{-1})^{-1}}{B(y_t+1,\kappa^{-1})}\frac{\kappa^{\alpha_t+y_t}}{B(\alpha_t,\beta_t)}\frac{s^r\kappa^{r-1}exp(-sk)}{\Gamma(r)}\left[\int_0^\infty log(\mu_t)\frac{\mu_t^{\alpha_t+y_t-1}}{(1+\kappa\mu_t)^{y_t+\kappa^{-1}+\alpha_t+\beta_t}}d\mu_t\right]d\kappa$$

$$\mathbb{E}[log(\mu_t \mid D_t) = \frac{1}{p(y_t \mid D_{t-1})}\int_0^\infty \frac{(y_t+\kappa^{-1})^{-1}}{B(y_t+1,\kappa^{-1})}\frac{\kappa^{\alpha_t+y_t}}{B(\alpha_t,\beta_t)}\frac{s^r\kappa^{r-1}exp(-sk)}{\Gamma(r)}\left[\frac{B(\alpha_t+y_t,\beta_t+\kappa^{-1})}{\kappa^{\alpha_t+y_t}}(\psi(\alpha_t+y_t) - \psi(\beta_t+\kappa^{-1}) - log(\kappa))\right]d\kappa$$

$$\mathbb{E}[log(\mu_t \mid D_t) = \frac{1}{p(y_t \mid D_{t-1})}\int_0^\infty \frac{(y_t+\kappa^{-1})^{-1}}{B(y_t+1,\kappa^{-1})}\frac{B(\alpha_t+y_t,\beta_t+\kappa^{-1})}{B(\alpha_t,\beta_t)}\left[\psi(\alpha_t+y_t) - \psi(\beta_t+\kappa^{-1}) - log(\kappa)\right]\frac{s^r\kappa^{r-1}exp(-sk)}{\Gamma(r)}d\kappa$$

□

Result (27):

$$\mathbb{E}[log^2(\mu_t) \mid D_t] = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty \frac{1}{y_t + \kappa^{-1}} \frac{1}{B(y_t+1, \kappa^{-1})} \frac{B(\alpha_t + y_t, \beta_t + \kappa^{-1})}{B(\alpha_t, \beta_t)}$$
$$\times \left[(\psi(\alpha_t + y_t) - \psi(\beta_t + \kappa^{-1}) - log(\kappa))^2 + \psi'(\alpha_t + y_t) + \psi^{'}(\beta_t + \kappa^{-1}) \right]$$
$$\times \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa.$$

Proof. Again, using the posterior for μ_t and Fubini's theorem we have that:

$$E[log^2(\mu_t) \mid D_t] = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty log^2(\mu_t) \int_0^\infty \frac{(y_t + \kappa^{-1})^{-1}}{B(y_t+1, \kappa^{-1})} \frac{\kappa^{\alpha_t + y_t}}{B(\alpha_t, \beta_t)} \frac{\mu_t^{\alpha_t + y_t - 1}}{(1 + \kappa\mu_t)^{y_t + \kappa^{-1} + \alpha_t + \beta_t}} \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa d\mu_t$$

$$E[log^2(\mu_t) \mid D_t] = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty \frac{(y_t + \kappa^{-1})^{-1}}{B(y_t+1, \kappa^{-1})} \frac{\kappa^{\alpha_t + y_t}}{B(\alpha_t, \beta_t)} \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) \left[\int_0^\infty log^2(\mu_t) \frac{\mu_t^{\alpha_t + y_t - 1}}{(1 + \kappa\mu_t)^{y_t + \kappa^{-1} + \alpha_t + \beta_t}} d\mu_t \right] d\kappa$$

$$E[log^2(\mu_t) \mid D_t] = \frac{1}{p(y_t \mid D_{t-1})} \int_0^\infty \frac{(y_t + \kappa^{-1})^{-1}}{B(y_t+1, \kappa^{-1})} \frac{B(\alpha_t + y_t, \beta_t + \kappa^{-1})}{B(\alpha_t, \beta_t)} \left[(\psi(\alpha_t + y_t) - \psi(\beta_t + \kappa^{-1}) - log(\kappa))^2 + \psi'(\alpha_t + y_t) + \psi^{'}(\beta_t + \kappa^{-1}) \right] \frac{s^r}{\Gamma(r)} \kappa^{r-1} exp(-s\kappa) d\kappa$$

□

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Pareceristas 2019

Nossos pareceristas do ano de 2019

A RSP agradece os atentos leituras e pertinentes observações de

Acir Almeida, Adalmir Gomes, Agatha Justen Gonçalves Ribeiro, Alberto Luiz Albertin, Aleksandra Santos, Alessandra de Linhares Jacobsen, Alexandre Cateb, Alexandre Laval Silva, Alexandre Sampaio Ferraz, Aline Lourenço de Oliveira, Alvaro Martim Guedes, Alvaro Martim Guedes, Ana Carolina Giuberti, Ana Claudia Moreira Cardoso, Ana Cláudia Niedhardt Capella, Ana Júlia Possamai, Ana Karruz, André Carraro, André de Oliveira, André Lugon, André Luís Bertassi, André Luiz Reis, André Marenco, Anete Brito Leal Ivo, Annita Calmon Mendes, Antonio Augusto Pereira Prates, Antonio Claret, Antonio Fernando Vieira Ney, Antonio Luiz Martins dos Reis, Ari Francisco de Araújo Jr, Assuero Ximenes, Benjamin Tabak, Biancca Scarpeline de Castro, Caio Rostirolla, Carlos Eduardo Cardoso de Oliveira, Carlos Wellington Leite de Almeida, Carolina Rocha, Carolina Tokarski, Cecília Olivieri, Christian Mendes, Ciro Fernandes, Claudio Burian Wanderley, Cláudio Gonçalves Couto, Claudio Luis de Camargo Penteado, Cledinaldo Dias, Clezio Saldanha dos Santos, Cristiane Bernardes, Cristiano Rocha Heckert, Daniel Oppermann, Daniela Peixoto Ramos, Dayane Gomes da Silva, Debora Cristina Rezende Almeida, Douglas Mendosa, Durval Lucas dos Santos Júnior, Edson Arlindo Silva, Eduardo Gomes, Elaine de Jesus Souza, Eleonora Schettini Martins Cunha, Elisabete Ferrarezi, Enrique Natalino, Erivelton Pires Guedes, Everton das Neves Gonçalves, Fabiano Maury Raupp, Fábio Grigoletto, Fábio Lotti Oliva, Fátima Bayma de Oliveira, Felipe Ribeiro Garcia, Felipe Silveira Marques, Felix Lopes, Fernando de Souza Coelho, Fernando Filgueiras, Flávia Mori Sarti, Flávia Regina Czarneski, Gabriela Lotta, Galba Moita, Gemael Chaebo, Geovana Prante Gasparotto, Geralda Luiza de Miranda, Gibran Teixeira, Gildete Dutra Emerick, Gilson Ditzel Santos, Heitor Frúgoli Junior, Helder Henrique Martins, Hélio Janny Teixeira, Ítalo de Paula Casemiro, Ivan Antônio Pinheiro, Ivan Beck Ckagnazaroff, Ivan Rocha Neto, Jacqueline Echeverría Barrancos, Jairo Eduardo Borges-Andrade, Janilson Antonio da Silva Suzart, Jeferson Goularte, Jefferson Lopes La Falce, João Estevão Barbosa Neto, Joaquim Rubens Fontes Filho, José Antonio Gomes de Pinho, José Carlos Martines Belieiro Junior, José Dantas, José de Oliveira, José Henrique Artigas de Godoy, José Geraldo Leandro, José Mancinelli Ledo do Nascimento, José Veríssimo Romão Netto, Júlia Rodrigues, Júlio Cesar Andrade de Abreu, Keicielle Schimidt de Oliveira, Laura Ibiapina Parente, Leandro Molhano Ribeiro, Leila Giandoni Ollaik, Leon Victor de Queiroz Barbosa, Leonardo Barbosa e Silva, Leonardo Bezerra, Leonardo Monteiro Monasterio, Leonel Oliveira, Leticia Bartholo, Lidiane Nazaré da Silva Dias, Lindomar Pinto da Silva, Lizandra Serafim, Lúcia de Fátima Nascimento de Queiroz, Luciana de Barros Jaccoud, Luciana Leite Lima, Luciana Stocco Betiol, Luciana Yeung, Luiz Alberto dos Santos, Luiz Antonio Abrantes, Luiz Carlos Fumiaki Miwa, Malena Rehbein Rodrigues, Marcelo Larratea, Marcia Alemão, Márcia Miranda Soares, Marco Antonio Alves, Marcos Gonçalves da Silva, Marcos Rosa, Marcus Vinicius Gonçalves da Cruz, Maria Beatriz Bettencourt, Maria do Carmo de Albuquerque Braga, Maria Luiza Levi Pahim, Maria Marconiete Fernandes Pereira, Maria Reis, Mariana Guerra, Marilia Ramos, Marina Félix de Melo, Marizaura Camões, Marta Maria Assumpção Rodrigues, Marta Zorzal e Silva, Martin Francisco de Almeida Fortis, Martin Wissmann, Maurício Soares Bugarin, Maurício de Faria, Maurício Michel Rebello, Mauro Silva, Michelle Graciela Morais de Sá e Silva, Miguel Loureiro, Milton Cordeiro Farias Filho, Mirela Castro Santos Camargos, Mirelle Cristina de Abreu Quintela, Monique Menezes, Monize Visentini, Natália de Oliveira Fontoura,Natália Guimarães Duarte Sátyro, Natália Massaco Koga, Nathalia Albuquerque, Osmany Porto de Oliveira, Oswaldo Gonçalves Junior, Otavio Prado, Patricia Amelia Tomei, Paula Chies Schommer, Pedro Célio Alves Borges, Pedro Masson, Pedro Paulo Murce Meneses, Pedro Resende Junior, Pery Francisco Assis Shikida, Philipe Marques, Rafael Kruter Flores, Rafael Silveira e Silva, Raphael Schlickmann, Regina Luna de Souza, Regis Augusto Ely, Rejane Sartori, Renata Bichir, Ricardo Antonio de Souza Karam, Ricardo de João Braga, Ricardo Gomes, Ricardo Mendonça, Rita de Cássia Marques Lima de Castro, Roberto Miranda, Roberto Pires, Robson Sávio Reis Souza, Rochelle de Souza, Rodrigo Nobre Fernandez, Rodrigo Rezende Ferreira, Rodrigo Rodrigues, Rogério Silva, Rogério Tadeu da Silva, Rubens de Oliveira Martins, Sabino da Silva Porto Jr, Sandra Oliveira Teixeira, Sheila Cristina Tolentino Barbosa, Silvia Generali da Costa, Teresa Sacchet, Tereza Cristina Silva Cotta, Thiago Aparecido Trindade, Thiago Lima da Silva, Tomas de Aquino Guimarães, Valdemir Aparecido Pires, Valdir Anhucci, Vanessa Elias de Oliveira, Victor Cláudio Paradela Ferreira, Victor Schmidt Comitti, Wagner Pralon Mancuso, Walmer Faroni, Wilson da Silva Gomes e Yves Basto Zamboni Filho

Idioma

English

Português (Brasil)

Español (España)

Enviar Submissão

6 de aproximadamente 67

[RSP] Agradecimento pela avaliação

Caixa de entrada ×

Claudio Djissey Shikida <pesquisaenap@enap.gov.br>

para mim

qua., 23 de out. de 2019 03:42

Caro(a) Victor Schmidt,

Agradecemos ter concluído a avaliação da submissão "Leilões para conversão de dívida em investimento" à revista Revista do Serviço Público.

Sua contribuição é fundamental para a qualidade dos trabalhos publicados.

Atenciosamente,

Claudio Djissey Shikida
Enap
pesquisaenap@enap.gov.br

Responder

Encaminhar

claudio.shikida@enap.gov.br

[RSP] Agradecimento pela avaliação

Caixa de entrada ×

Claudio Djissey Shikida <claudio.shikida@enap.gov.br>

para mim

qui., 5 de set. de 2019 03:49

Caro(a) Victor Schmidt,

Agradecemos ter concluído a avaliação da submissão "POLÍTICA DE CAPACITAÇÃO DA UNIVERSIDADE FEDERAL DE ALAGOAS" à revista Revista do Serviço Público.

Sua contribuição é fundamental para a qualidade dos trabalhos publicados.

Atenciosamente,

Claudio Djissey Shikida
Enap
claudio.shikida@enap.gov.br

Responder

Encaminhar

SUPERINTENDÊNCIA-REGIONAL SUDESTE I EM SÃO PAULO
GERÊNCIA EXECUTIVA - B - ARARAQUARA
SEÇÃO OPERACIONAL DA GESTÃO DE PESSOAS

PORTARIA Nº 56, DE 3 DE JULHO DE 2019

A Chefe da Seção Operacional da Gestão de Pessoas, da Gerência Executiva do INSS em Araraquara/SP, no uso das atribuições conferidas no inciso I, do artigo 235 do Regimento Interno aprovado, pela Portaria MDS nº 414 de 28/09/2017, publicada no DOU nº 188-A, de 29/09/2017, conforme Processo 37298.000131/2019-27,resolve:

Conceder Aposentadoria Voluntária Integral, ao servidor VALDINO RAMOS - SIAPE 0568475, ocupante do cargo de Administrador, Classe S, Padrão IV, do quadro de pessoal do Instituto Nacional do Seguro Social, com fundamento no artigo 3º da Emenda Constitucional 47/2005, com os proventos integrais, acrescidos das demais vantagens a que faz jus, com opção pela incorporação da Gratificação de Desempenho aos proventos de aposentadoria nos termos dos artigos 88 a 92 da Lei 13324/2016.Declarar vago, o referido cargo.

MARA SILVIA SOUZA MIRANDA

SUPERINTENDÊNCIA REGIONAL SUL EM FLORIANÓPOLIS
GERÊNCIA EXECUTIVA - B - CRICIÚMA
SEÇÃO OPERACIONAL DA GESTÃO DE PESSOAS

PORTARIA Nº 50, DE 18 DE JULHO DE 2019

A CHEFE SUBSTITUTA DA SEÇÃO OPERACIONAL DA GESTÃO DE PESSOAS DA GERÊNCIA EXECUTIVA DO INSS EM CRICIÚMA/SC, designada pela PT Nº 57/GEXCRI/INSS/SC, de 26/12/2018, publicada no BSL nº 51, de 26/12/2018, e no uso das atribuições que lhe confere o artigo 235, do Regimento Interno desta autarquia, aprovado pela Portaria PT/MDS nº 414, de 28 de setembro de 2017, publicada no Diário Oficial da União nº 188-A, de 29 de setembro de 2017, resolve:

Conceder aposentadoria voluntária integral a servidora LIZANDRA HULSE DE FARIAS matrícula SIAPE nº 929362, ocupante do cargo de Tecnico do Seguro Social, código 434550, nível "NI", classe "S", padrão "IV", do quadro de pessoal do INSS, com fundamento no art. 3º da Emenda Constitucional nº 47, de 5 de julho de 2005, observado o contido no processo nº 35344.000133/2019-98, declarando, em consequência, o referido cargo vago.

MARILDA RIBEIRO DOS SANTOS

SUPERINTENDÊNCIA DE SEGUROS PRIVADOS
SECRETARIA-GERAL

PORTARIA Nº 7.412, DE 17 DE JULHO DE 2019

A SUPERINTENDENTE DA SUPERINTENDÊNCIA DE SEGUROS PRIVADOS - SUSEP, no uso das atribuições que lhe confere o inciso VI do art. 30 da Portaria Susep nº 7.371, de 29 de maio de 2019, e conforme o inciso I do art. 9º da Portaria GME nº 10, de 17 de janeiro de 2019, resolve:

Art. 1º Nomear a servidora THERESA CHRISTINA CUNHA MARTINS, CPF 363.428.587-72, para exercer a função de Chefe da Secretaria do CRSNSP - SESEC, código DAS 101.1, na estrutura do Gabinete - GABIN.

Art. 2º Esta Portaria entra em vigor na data de sua publicação.

SOLANGE PAIVA VIEIRA

SUPERINTENDÊNCIA DA ZONA FRANCA DE MANAUS

PORTARIA N° 563, DE 16 DE JULHO DE 2019

O SUPERINTENDENTE DA SUPERINTENDÊNCIA DA ZONA FRANCA DE MANAUS, no uso da competência que lhe foi subdelegada pela Portaria nº 10, de 17 de janeiro de 2019, e considerando o disposto no Decreto nº 7.139, de 29 de março de 2010, com suas alterações, na Portaria nº 83-SEI, de 12 de janeiro de 2018 e na Lei nº 8.112, de 11 de dezembro de 1990, e os termos constantes do Processo SEI nº 52710.006121/2019-71, resolve:

Art. 1º Designar DANIEL LIMA DA SILVA FILHO, Matrícula SIAPE nº 1632977, para exercer a Função Comissionada do Poder Executivo Federal de Coordenador-Geral de Execução Orçamentária e Financeira, código FCPE 101.4, da Superintendência Adjunta Executiva, da Superintendência da Zona Franca de Manaus, ficando, por consequência, dispensado do encargo de Coordenador Geral substituto que atualmente exerce.

Art. 2º Dispensar CARLITO DE HOLANDA SOBRINHO, Matrícula SIAPE nº 1082665, da Função Comissionada do Poder Executivo Federal de Coordenador-Geral de Execução Orçamentária e Financeira, código FCPE 101.4, da Superintendência Adjunta Executiva, da Superintendência da Zona Franca de Manaus.

Art. 3º Designar CARLITO DE HOLANDA SOBRINHO, Matrícula SIAPE nº 1082665, para exercer o encargo de Coordenador-Geral, substituto, da Coordenação-Geral de Execução Orçamentária e Financeira, código FCPE 101.4, da Superintendência Adjunta Executiva, da Superintendência da Zona Franca de Manaus, nos afastamentos e impedimentos legais e regulamentares do titular do cargo.

Art. 4º Esta Portaria entra em vigor na data de sua publicação.

ALFREDO ALEXANDRE DE MENEZES JÚNIOR

PORTARIA N° 569, DE 18 DE JULHO DE 2019

O SUPERINTENDENTE DA SUPERINTENDÊNCIA DA ZONA FRANCA DE MANAUS, no uso da competência que lhe foi subdelegada pelo Art. 9º, da Portaria GM/ME nº 10, de 17 de janeiro de 2019, e considerando o disposto no Decreto nº 7.139, de 29 de março de 2010, com suas alterações, na Portaria nº 83-SEI, de 12 de janeiro de 2018 e na Lei nº 8.112, de 11 de dezembro de 1990, no Decreto 9.727 e Decreto 9.732, de março de 2019, e os termos do Processo nº 52710.006377/2019-88, resolve:

Art. 1º Exonerar, a pedido, EMMANUEL RIBEIRO SALES DE AGUIAR, Matrícula SIAPE nº 677898, do Cargo em Comissão de Coordenador-Geral de Planejamento e Programação Orçamentária, código DAS 101.4, da Superintendência Adjunta de Planejamento e Desenvolvimento Regional.

Art. 2º NOMEAR FÁBIO LEANDRO CALDERARO, CPF nº 212.549.178-88, para exercer o Cargo em Comissão de Coordenador-Geral de Planejamento e Programação Orçamentária, código DAS 101.4, da Superintendência Adjunta de Planejamento e Desenvolvimento Regional, da Superintendência da Zona Franca de Manaus.

Art. 3º Esta Portaria entra em vigor na data de sua publicação.

ALFREDO ALEXANDRE DE MENEZES JÚNIOR

BANCO NACIONAL DE DESENVOLVIMENTO ECONÔMICO E SOCIAL

DESPACHO DE 15 DE JULHO DE 2019

Afastamento do País autorizado pelo Diretor Roberto Carlos Marucco Junior em 15/07/2019, de acordo com a subdelegação de competência prevista na Portaria PRESI nº 110/2017-BNDES, de 04/04/2017, do Presidente do BNDES: FELIPE BUCHBINDER, engenheiro, para realizar mestrado na Duke University, em Durham/EUA, no período de 29/07/2019 a 05/08/2021, inclusive trânsito, com ônus (Processo de Viagem ao Exterior nº 63714).

ROBERTO CARLOS MARUCCO JUNIOR
Diretor

FUNDAÇÃO ESCOLA NACIONAL DE ADMINISTRAÇÃO PÚBLICA
DIRETORIA DE GESTÃO INTERNA
COORDENAÇÃO DE RECURSOS HUMANOS

PORTARIA Nº 436, DE 18 DE JULHO DE 2019

O PRESIDENTE DA FUNDAÇÃO ESCOLA NACIONAL DE ADMINISTRAÇÃO PÚBLICA - ENAP, no uso das atribuições que confere o Estatuto aprovado pelo Decreto n° 9.680, de 2 de janeiro de 2019, considerando o Regulamento do Programa Cátedras Brasil, instituído pela Resolução n° 26, de 06 de agosto de 2018, e o disposto no Edital n° 50, de 11 de junho de 2019, resolve:

Art. 1° Instituir a Comissão Julgadora tendo em vista a seleção de candidatos para concessão de bolsas de pesquisa e de inovação do Edital n° 50/2019, composta pelos seguintes membros titulares e suplentes:

I - Claúdio Djissey Shikida (Presidente)
II - André Carraro
III - Antônio Claret Campos Filho
IV - Aumara Bastos Feu Alvim de Souza
V - Bernardo Lanza Queiroz
VI - Ciro Campos Christo Fernandes
VII - Daienne Amaral Machado
VIII - Eduardo Pontual Ribeiro
IX - Erik Alencar de Figueiredo
X - Everson Lopes de Aguiar
XI - Frank Magalhães de Pinho
XII - Igor Vinicius de Souza Geracy
XIII - João Paulo de Resende
XIV - Leonardo Carvalho de Mello
XV - Luanna Sant'Anna Roncaratti
XVI - Luciano Benetti Timm
XVII - Marize Schons
XVIII - Maurício Mota Saboya Pinheiro
XIX - Natália Massaco Koga
XX - Nelson Leitão Paes
XXI - Pedro Henrique Costa Gomes de Sant'Anna
XXII - Regina Luna de Santos Souza
XXIII - Ricardo de Lins e Horta
XXIV - Roberta da Silva Vieira
XXV - Rodrigo Leandro de Moura
XXVI - Thais Gargantini Cardarelli
XXVII - Thomas Victor Conti
XXVIII - Victor Schimidt Comitti
XXIX - Wanderson Maia Nascimento
XXX - Wilsimara Maciel Rocha

Art. 2° A Comissão Julgadora terá as seguintes atribuições:

I - Avaliar os projetos de pesquisa e inovação submetidos para o Edital nº 50/2019, conforme os critérios de julgamento constantes no Anexo II do Edital;

II - Realizar, quando cabível, entrevistas com os candidatos aprovados na primeira fase do processo de seleção (análise dos projetos de pesquisa) do Edital nº 50/2019;

III - Avaliar as entrevistas realizadas com os candidatos do Edital nº 50/2019, conforme os critérios de julgamento constantes no Anexo II do Edital e;

IV - Manifestar-se, oportunamente, em face da interposição de recursos relativos ao Edital nº 50/2019, conforme os itens 8.3 do Edital e 10.3 do Regulamento (Anexo I do Edital).

Art. 3° Esta Portaria entra em vigor na data de sua publicação.

DIOGO G. R. COSTA

FUNDAÇÃO JORGE DUPRAT FIGUEIREDO, DE SEGURANÇA E MEDICINA DO TRABALHO

PORTARIA Nº 265, DE 18 DE JULHO DE 2019

O PRESIDENTE DA FUNDAÇÃO JORGE DUPRAT FIGUEIREDO, DE SEGURANÇA E MEDICINA DO TRABALHO DO MINISTÉRIO DA ECONOMIA, no uso de suas atribuições e considerando a subdelegação de competência de que trata o inciso VIII do art. 9º da Portaria GM/MECON nº 10, de 17 de janeiro de 2019, publicada no Diário Oficial da União de 18 de janeiro de 2019, alterada pela Portaria GM/MECON nº 18, de 28 de janeiro de 2019, publicada no Diário Oficial da União de 29 de janeiro de 2019, resolve:

Designar ALLAN DAVID SOARES, CPF nº ***.262.338-**, matrícula nº 2999242, para exercer o encargo de substituto eventual da Diretora-Executiva, código DAS 101.5, desta Fundação Jorge Duprat Figueiredo de Segurança e Medicina do Trabalho - FUNDACENTRO, nos seus afastamentos ou impedimentos regulamentares, sem prejuízo das respectivas atribuições.

FELIPE MÊMOLO PORTELA

Ministério da Educação

GABINETE DO MINISTRO

PORTARIA Nº 1.374, DE 18 DE JULHO DE 2019

O MINISTRO DE ESTADO DA EDUCAÇÃO, no uso da atribuição que lhe confere o art. 87, parágrafo único, inciso IV, da Constituição, e em observância ao disposto na Lei nº 8.112, de 11 de dezembro de 1990, no Decreto nº 8.956, de 12 de janeiro de 2017, no Decreto nº 9.665, de 02 de janeiro de 2019 bem como no inciso II, art. 6º do Decreto no 9.794, de 14 de maio de 2019, resolve:

EXONERAR RENATO AUGUSTO DOS SANTOS, CPF nº 169.549.198-02, do cargo de Coordenador-Geral, código DAS-101.4, da Coordenação-Geral de Controle de Qualidade da Educação Superior, da Diretoria de Avaliação da Educação Superior, do Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira, a contar de 10 de julho de 2019.

ABRAHAM WEINTRAUB

DIÁRIO OFICIAL DA UNIÃO

Publicado em: 19/07/2019 | Edição: 138 | Seção: 2 | Página: 21

Órgão: Ministério da Economia/Fundação Escola Nacional de Administração Pública/Diretoria de Gestão Interna/Coordenação de Recursos Humanos

PORTARIA Nº 436, DE 18 DE JULHO DE 2019

O PRESIDENTE DA FUNDAÇÃO ESCOLA NACIONAL DE ADMINISTRAÇÃO PÚBLICA - ENAP, no uso das atribuições que confere o Estatuto aprovado pelo Decreto n° 9.680, de 2 de janeiro de 2019, considerando o Regulamento do Programa Cátedras Brasil, instituído pela Resolução n° 26, de 06 de agosto de 2018, e o disposto no Edital n° 50, de 11 de junho de 2019, resolve:

Art. 1° Instituir a Comissão Julgadora tendo em vista a seleção de candidatos para concessão de bolsas de pesquisa e de inovação do Edital n° 50/2019, composta pelos seguintes membros titulares e suplentes:

I - Claúdio Djissey Shikida (Presidente)

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XXI - Pedro Henrique Costa Gomes de Sant'Anna

XXII - Regina Luna de Santos Souza

XXIII - Ricardo de Lins e Horta

XXIV - Roberta da Silva Vieira

XXV - Rodrigo Leandro de Moura

XXVI - Thais Gargantini Cardarelli

XXVII - Thomas Victor Conti

XXVIII - Victor Schimidt Comitti

XXIX - Wanderson Maia Nascimento

XXX - Wilsimara Maciel Rocha

Art. 2° A Comissão Julgadora terá as seguintes atribuições:

I - Avaliar os projetos de pesquisa e inovação submetidos para o Edital nº 50/2019, conforme os critérios de julgamento constantes no Anexo II do Edital;

II - Realizar, quando cabível, entrevistas com os candidatos aprovados na primeira fase do processo de seleção (análise dos projetos de pesquisa) do Edital nº 50/2019;

III - Avaliar as entrevistas realizadas com os candidatos do Edital nº 50/2019, conforme os critérios de julgamento constantes no Anexo II do Edital e;

IV - Manifestar-se, oportunamente, em face da interposição de recursos relativos ao Edital nº 50/2019, conforme os itens 8.3 do Edital e 10.3 do Regulamento (Anexo I do Edital).

Art. 3° Esta Portaria entra em vigor na data de sua publicação.

DIOGO G. R. COSTA

Certificado de Apresentação de Trabalho

Certificamos que o trabalho " *Bayesian Dynamic Models for Count Data with Overdispersion and Inflation of Zeros*" de autoria de Victor Schmidt Comitti , Thiago Rezende dos Santos , Fabio Nogueira Demarqui , aprovado na categoria Comunicação Pôster foi apresentado no evento 18th ESTE - Time Series and Econometrics Meeting, Gramado (RS), Brazil September 3-6, 2019 , realizado em Serra Azul Hotel, Gramado (RS), Brazil, entre os dias 03/09/2019 e 06/09/2019.

Atenciosamente,

Comissão Organizadora

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Associação Brasileira de Estatística

CNPJ: 56572456/0001-80

Caixa Postal 66281

05315-970 São Paulo/SP.

Certificado de participação

Certificamos que Victor Schmidt Comitti participou do 18th ESTE - Time Series and Econometrics Meeting, Gramado (RS), Brazil September 3-6, 2019 realizado em Serra Azul Hotel, Gramado (RS), Brazil no período de 03/09/2019 a 06/09/2019

Cursos:

- Statistical Learning
- Importação on-line de séries temporais econômicas e financeiras usando R

São Paulo, 13 de Setembro de 2019
Comissão Organizadora

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Associação Brasileira de Estatística

CNPJ: 56572456/0001-80

Caixa Postal 66281

05315-970 São Paulo/SP.

DECLARAÇÃO

Declaro para os devidos fins que Victor Schimitti Comitti participou da organização do IFPLAYERS 2019 no segundo semestre de 2019.

Bom Sucesso, 18 de março de 2020

ASSINADO E/OU AUTENTICADO PELO PROFESSOR GRAZIANY THIAGO FONSECA
SIAPE 19669046

Coordenador do curso de Análise e Desenvolvimento de Sistemas

Boletim de Gestão de Pessoas
Brasília, 18 de fevereiro de 2019 ISSN 1111-1111 Ano 3 Número 2.11

INSTITUTO FED.DO SUDESTE DE MINAS GERAIS

Rei-gabinete Da Reitoria

PORTARIA nº 230, de 13 de fevereiro de 2019

O **Reitor do Instituto Federal de Educação, Ciência e Tecnologia do Sudeste de Minas Gerais**, no uso de suas atribuições legais, conferidas pelo Decreto Presidencial de 12-04-2017, publicado no Diário Oficial da União, Edição nº 72, de 13-04-2017, Seção 2, página 01, e, ainda, *considerando* o Memorando Eletrônico n° 5/2019 - BSCCAMPUS, de 12-02-2019, Identificador 201933887, resolve:

Art. 1º- **DESIGNAR** os servidores abaixo relacionados para comporem a Subcomissão Permanente de Pessoal Docente (SPPD) do IF Sudeste MG - *Campus* Avançado Bom Sucesso, conforme a seguir:

Nome	*Siape*	*Representatividade*
Robson José da Silva	2047063	Presidente
Telma Suely da Silva Morais	3078817	Membro Titular
Victor Schmidt Comitti	3082930	Membro Titular
Danielle Pereira Baliza	1953999	Membro Suplente
Wilker Rodrigues de Almeida	1847521	Membro Suplente
José Alves Junqueira Júnior	1550608	Membro Suplente

Art. 2º- **REVOGAR** a Portarias-R nºs 597/2016, de 01-07-2016, e 948/2017, de 04-08-2017.

CHARLES OKAMA DE SOUZA

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